The Use of Social Media in Enterprises for Communication, Collaboration, and Knowledge Management

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Marburg, 16.12.2015

Tobias H. Engler

Inhalt der kumulativen Dissertationsschrift

Leserführung

Die vorliegende kumulative Inauguraldissertation wurde gemäß § 8 der Promotionsordnung des Fachbereichs Wirtschaftswissenschaften der Philipps-Universität Marburg vom 8. Juni 2009 erstellt und besteht aus acht Essays.

Die enthaltenen Essays I, II, III, IV und V wurden bereits in wissenschaftlichen Zeitschriften oder in Tagungsbänden veröffentlicht. Die Essays VI, VII und VIII sind bei verschiedenen wissenschaftlichen Zeitschriften zur Veröffentlichung eingereicht. Aufgrund der unterschiedlichen Publikationsarten besteht keine einheitliche Formatierung. Die Formatierungen entsprechen denen der veröffentlichten Artikel oder den geforderten Formatierungen der Einreichungen. Auf eine nachträgliche Änderung der veröffentlichten und eingereichten Essays und die Einführung einer übergreifenden Seitenzahl wurde verzichtet, um den Originalzustand der Artikel wiederzugeben. Die Essays sind chronologisch anhand des Erscheinungs- beziehungsweise Einreichungsdatums sortiert.

Inhaltliche Zusammenführung

Einleitung

Der Erfolg von Social Media im Internet hat dazu geführt, dass diese Technologie zunehmend auch in Unternehmen eingesetzt oder dass über deren Implementierung nachgedacht wird. Durch die erwartete Verbesserung der Kommunikation und Interaktion zwischen Mitarbeitern auf der einen Seite und des Wissensmanagements auf der anderen Seite erhoffen sich Entscheidungsträger in Unternehmen einen erheblichen betriebswirtschaftlichen Nutzen (vgl. Turban et al. 2011). Obwohl es einige Beispiele erfolgreicher Enterprise-Social-Media(ESM)-Implementierungen gibt (vgl. Turban et al. 2011) und mehr als 90% der Fortune 500 Unternehmen ESM eingeführt haben oder dies planen (Deloitte 2013), verfehlen 80% der ESM-Projekte die eingangs definierten Ziele (Gartner 2013). Während die Entscheidung, die Software einzukaufen, zentral getroffen wird, hängt deren Erfolg von der aktiven Partizipation der Mitarbeiter ab – wie sich anhand der genannten Statistiken zeigt, ist beides nicht zwangsläufig korreliert. Im Gegensatz zu organischem Wachstum, wie es in Social-Media-Anwendungen im Internet in den vergangenen Jahren beobachtet werden konnte (z.B. bei Facebook), ist die Nutzungsrate von internen ESM oft zu gering, um den Fortbestand der Community zu sichern. Es zeigt sich dabei verstärkt, dass passive Roll-Out-Strategien, die darauf vertrauen, dass es ein vergleichbares organisches Wachstum auch bei ESM gibt, zum Scheitern verurteilt sind (McAfee 2009). Vielmehr müssen Analysen im Vorhinein das für einen spezifischen Anwendungsbereich geeignete Tool identifizieren und es müssen Strategien entwickelt werden, wie Mitarbeiter für die Interaktion über die neuen Anwendungen gewonnen werden können.

Da Ausgaben für Informationstechnologien bei einem geringen Nutzungsgrad nicht zu rechtfertigen sind (Agarwal and Prasad 1997), soll die vorliegende Dissertation in acht Essays verschiedene Facetten der ESM-Nutzung näher beleuchten und so zu einem besseren Verständnis des Themas und damit einhergehend einer effektiveren und effizienteren Implementierung von ESM beitragen. Sowohl die Analyse von Einflussfaktoren auf verschiedene Nutzungstypen von ESM, die Optimierung von Enterprise-Suchalgorithmen als auch die Neuinterpretation von Online-Produkt-Ratings können dabei helfen, die Veränderungen der internen und externen Kommunikation, Kollaboration und des Wissensmanagements, die sich durch den Einsatz von ESM ergeben, besser zu erklären und bedarfsgerechter einzusetzen. Die theoretischen und praktischen Implikationen, welche sich konkret aus den einzelnen Essays ergeben, werden in den entsprechenden Abschnitten der jeweiligen Papiere erläutert. Die inhaltliche Zusammenführung soll die Zusammenhänge der einzelnen Essays zum Promotionsthema und untereinander darstellen. Dazu werden zuerst ESM-Technologien und Anwendungsbereiche im Allgemeinen erläutert und hieraus im Anschluss ein Rahmen zur Einordnung der Essays I-VIII abgeleitet.

Enterprise Social Media

ESM-Tools

McAfee (2006), der den Begriff „Enterprise 2.0" für den Einsatz von Social Media in Unternehmen einführte, beschreibt ESM als soziale Technologien, die auf einer Sammlung von Web 2.0-Anwendungen beruhen und im Unternehmen eingesetzt werden, um dort unterschiedliche Aufgaben zu unterstützen. Web 2.0-Anwendungen sind wiederum Internet-Technologien, die die Erstellung und den Austausch von usergeneriertem Inhalt ermöglichen (Kaplan und Haenlein 2010). Zu den Anwendungen, die auch im Unternehmen eingesetzt werden, gehören soziale Profile, Activity Streams, (Micro-)Blogging, Enterprise Search, Rating und Reviews, Content Management Systeme, Gruppen und Communities, Instant Messaging und Social Tagging (vgl. Chin et al. 2015). Ein Überblick über die Technologien und eine Definition der für diese Arbeit relevanten Tools findet sich in Abbildung 1.

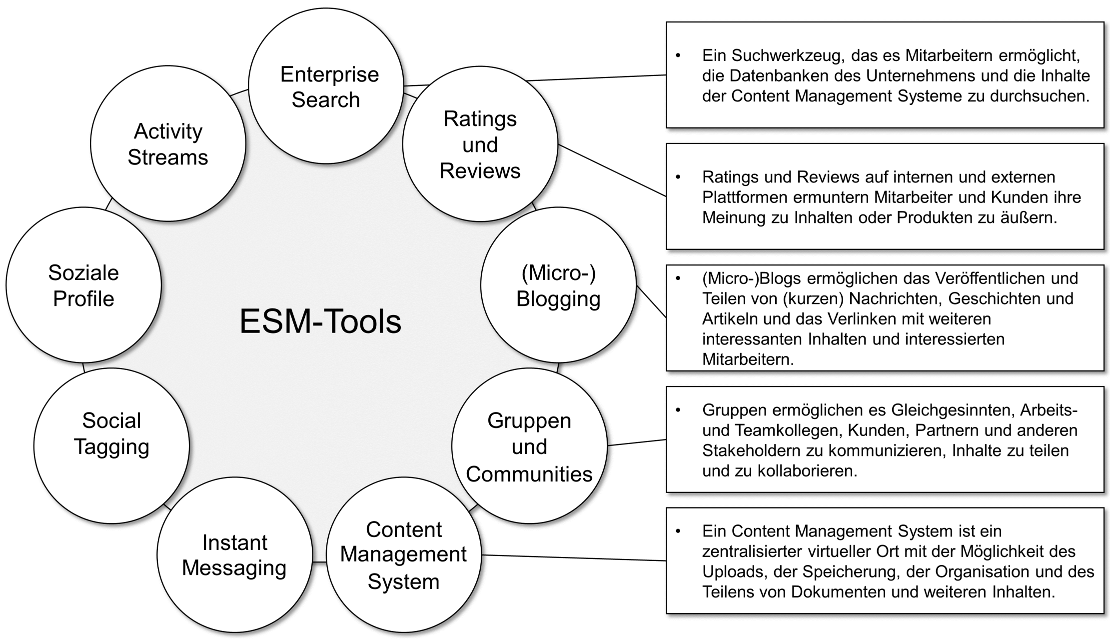

Abbildung 1: ESM-Tools (in Anlehnung an Chin et al. 2015)

Anwendungsbereiche von ESM

Neben den Anwendungen selbst lassen sich auch die Anwendungsbereiche von ESM-Tools unterscheiden. Eine grobe Untergliederung in interne und externe Anwendungen schlagen Leonardi et al. (2013) vor. Demnach können die Tools primär danach unterschieden werden, ob sie zur Kommunikation mit externen Stakeholdern wie zum Beispiel Kunden, Partnern und der Öffentlichkeit genutzt werden oder der internen Interaktion zwischen Mitarbeitern dienen. Die Kommunikation mit externen Stakeholdern über Social Media erfolgt meist über mehrere Plattformen wie Facebook, Twitter oder Google+ (Leonardi et al. 2013). Die interne Interaktion hingegen wird meist durch eine einzige Plattform unterstützt, die alle benötigten Funktionen enthält (McAfee 2009). Anbieter solcher integrierter Plattformen sind zum Beispiel Microsoft (Yammer, Sharepoint), IBM (IBM Connections) und Jive.

Eine weitere funktionale Gliederungsebene findet sich bei Turban et al. (2011). Die Autoren unterscheiden die Anwendungen nicht nach den Teilnehmern der Interaktion, sondern nach den Aufgaben, die durch die einzelnen Tools unterstützt werden. Die identifizierten Anwendungsbereiche sind: Kommunikation, Kollaboration, Wissensmanagement, Weiterbildung, Management-Aktivitäten und Problemlösung und Informationsverbreitung. Die Bereiche und einige Anwendungsbeispiele sind in Abbildung 2 dargestellt.

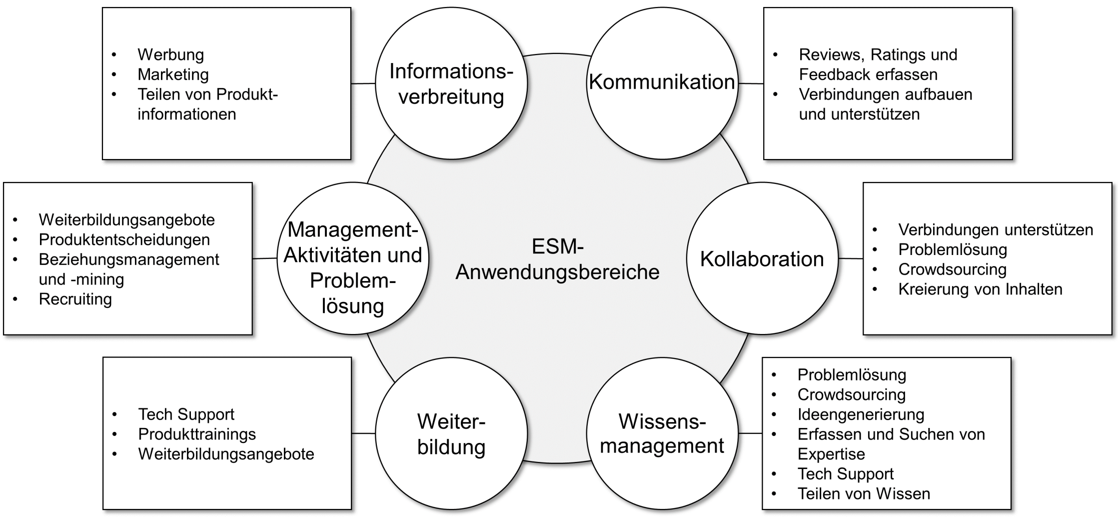

Abbildung 2: Anwendungsbereiche von ESM-Tools (in Anlehnung an Turban et al. 2011)

Einordnung und Zusammenfassung der Essays

Unter Einbezug der vorgestellten ESM-Tools und deren Anwendungsbereichen lässt sich eine Matrix aufspannen, in die die Essays I-VIII eingeordnet werden können. Die in Abbildung 3 dargestellte Matrix beinhaltet die für die vorliegende Arbeit relevanten Ausprägungen der Dimensionen ESM-Tools und Anwendungsbereiche.

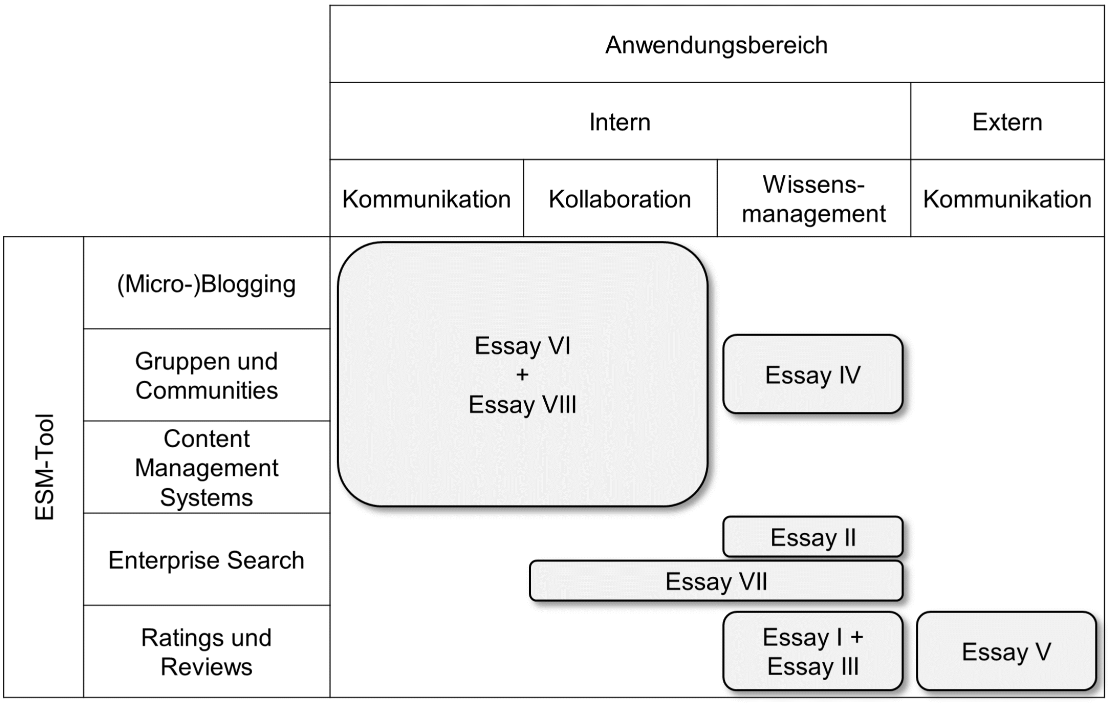

Abbildung 3: Einordnung der Essays

Nachfolgend sollen die Essays kurz eingeführt und deren Einordnung in der Matrix erläutert werden.

In Essay I wird ein theoretisches Modell vorgeschlagen, das die Rolle von Vertrauen in Experten- und Kollegen-Reviews während des Suchprozesses nach Wissen in internen sozialen Wissensmanagement-Tools (z.B. Wikis) näher beleuchtet (→ Matrixposition: Wissensmanagement und Ratings und Reviews). Dazu werden die Prädiktoren von Vertrauen einbezogen, das Ergebnis von Vertrauen in Reviews dargestellt und der Einfluss des wahrgenommenen Risikos, das mit der Wissensanwendung verbunden ist, theoretisch hergeleitet. Das Modell legt nahe, dass das Vertrauen in Experten- und Kollegen-Reviews auf der Fähigkeit, dem Wohlwollen und der Integrität der jeweiligen Reviewer-Gruppe basiert und positiv durch eine höhere Neigung des Wissenssuchers zu vertrauen beeinflusst wird. Das in einer bestimmten Situation wahrgenommene Risiko beeinflusst die Entscheidung, ob Wissen eher auf Basis von Experten- oder Kollegen-Reviews angewendet wird. Es wird angenommen, dass Wissensanwendung unter hohem Risiko eher auf Experten-Reviews basiert, da diese das organisationale und individuelle Risiko senken, während Reviews von Kollegen nur das organisationale Risiko mindern können.

In Essay II wird untersucht, wie die Integration von sozialen Daten die Suchalgorithmen von Wissensmanagement-Tools (am Beispiel eines Business-Intelligence(BI)-Systems) verbessern können (→ Matrixposition: Wissensmanagement und Enterprise Search). Dazu werden mögliche Variablen identifiziert und danach klassifiziert, ob es sich um berichtsbezogene, benutzerbezogene oder interaktionsbezogene Variablen handelt. Es wird beschrieben, wie sich die einzelnen Variablen auf die Relevanz eines Reports für den Nutzer der Suchfunktion auswirken. Diese Klassifizierung kann als Grundlage für die Entwicklung eines Suchalgorithmus für den Einsatz in BI-Portalen dienen.

Essay III beschreibt den Prozess, wie die Anzeige verschiedener sozialer Zusatzinformationen (z.B. Subscriptions) die wahrgenommene Nützlichkeit eines Berichts in einem Wissensmanagement-Tool (hier: BI-Portal) verändern (→ Matrixposition: Wissensmanagement und Ratings und Reviews). Die Analyse des Prozesses basiert auf dem „elaboration likelihood model", welches davon ausgeht, dass die wahrgenommene Nützlichkeit einer Information entweder von der Qualität der gezeigten Informationen oder peripheren Hinweisen beeinflusst wird. Die Erfahrung des Nutzers bestimmt dabei den Grad der Beeinflussung durch Qualität und periphere Hinweise. Ein Experiment mit Wissensarbeitern wurde durchgeführt, um das theoretische Modell empirisch zu überprüfen.

In Essay IV wird ein vertiefter Einblick in den Prozess des Beitragens von Wissen zur Ideengenerierung in Intranet-Communities gegeben (→ Matrixposition: Wissensmanagement und Communities). In dem Essay wird ein Modell präsentiert, das sowohl die anfängliche Bereitschaft Wissen in einer Intranet-Community zu teilen als auch das langfristige Beisteuern weiterer Beiträge erklärt. Die „theory of reasoned action", die „social exchange theory" und das „belief adjustment model" dienen als theoretische Basis für das Modell. Der erste Teil des Modells wird anhand einer Feldstudie empirisch überprüft.

Essay V baut auf der unter Praktikern und Forschern verbreiteten Annahme auf, dass Kunden durch Online-Produkt-Ratings ein Spiegelbild der Produktqualität kommuniziert wird. Das Essay versucht dieser Annahme eine zusätzliche Perspektive hinzuzufügen (→ Matrixposition: externe Kommunikation und Ratings und Reviews). In einem ersten Schritt wird theoretisch hergeleitet, dass Online-Ratings eher die Zufriedenheit des Kunden mit dem Produkt wiedergeben als die reine Evaluation der Qualität. Dementsprechend wird ein Kundenzufriedenheits-Modell von Online-Produkt-Ratings entwickelt, das die Erwartungen der Kunden vor dem Kauf und die tatsächliche Produktleistung als Determinanten der Bewertungen enthält. Das Modell wird anhand von zwei Datensätzen, die auf der deutschen Webseite von amazon.com gesammelt wurden, überprüft.

Essay VI konzentriert sich auf die Einführung von ESM-Plattformen für Kommunikation und Kollaboration (→ Matrixposition: interne Kommunikation/Kollaboration und Blogging/CMS/Gruppen und Communities). Während in Essay IV der Prozess des Wissensbeitragens untersucht wird, wird in diesem Papier ein Vergleich zwischen zwei Haupttypen der Anwendung von ESM vorgenommen: Der Beitrag und das Konsumieren von Inhalten innerhalb einer ESM-Plattform. Es wird angenommen, dass eine einzelne abhängige Variable in der Technologie-Akzeptanz-Forschung zu trügerischen Ergebnissen führen kann, wenn die untersuchte Technologie (z.B. eine ESM-Plattform) mehrere fundamental verschiedene Nutzungstypen unterstützt. Beide Arten der Nutzung werden mit Hilfe eines angepassten Technologie-Akzeptanz-Modells analysiert und die Differenzen herausgearbeitet.

Essay VII adressiert die unterschiedlichen Anforderungen von Suchalgorithmen innerhalb eines Unternehmens und der Web-Suche. Da im Intranet keine Linkstruktur zur Bewertung der Relevanz von Seiten und Dokumenten herangezogen werden kann, wird in Essay VII ein Referenzalgorithmus entwickelt, der die Relevanz von Dokumenten im Intranet anhand persönlicher, sozialer, kollaborativer und dynamischer Daten berechnet (→ Matrixposition: interne Kollaboration/Wissensmanagement und Enterprise Search). Im Anschluss an die Entwicklung wird eine typische Instanz dieses Algorithmus in einem Laborexperiment mit Studenten getestet.

In Essay VIII liegt der Fokus auf den Unterschieden zwischen Prädiktoren der Nutzungsabsicht von Blogs, sozialen Netzwerken und Wikis (→ Matrixposition: interne Kommunikation/Kollaboration und Blogging/CMS/Gruppen und Communities). Das dazu entwickelte Modell schließt technologische und individuelle Faktoren ein, die auf Erkenntnissen der Forschung über virtuelle Zusammenarbeit und Wissensaustausch basieren. Da verschiedene ESM-Tools grundsätzlich in verschiedenen Anwendungsbereichen eingesetzt werden können, werden durch die Identifizierung von „Uses & Gratifications“ Unterschiede zwischen den einzelnen Treibern der Akzeptanz der drei Tools erklärt. Drei, in einem internationalen Technologie-Unternehmen in der Pre-Implementierungsphase der ESM-Tools durchgeführte, parallele Feldstudien (eine für jedes Tool) dienen zur Überprüfung der hergeleiteten Hypothesen.

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Essay I

Titel

Trusting Review Mechanisms in Knowledge Management Systems: Antecedents, Outcomes, and the Role of Perceived Risk

Autor

- Tobias H. Engler

Konferenz

European Conference on Information Systems 2014, Tel-Aviv

Referenz

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TRUSTING REVIEW MECHANISMS IN KNOWLEDGE MANAGEMENT SYSTEMS: ANTECEDENTS, OUTCOMES, AND THE ROLE OF PERCEIVED RISK

Research in Progress

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Abstract

In recent years, the success of social media in the private realm has entailed an increasing awareness of opportunities that are linked to user-generated content in knowledge management systems. Alongside the benefits in terms of knowledge quantity, new quality risks arise from an unregulated knowledge contribution. Considering that, review mechanisms have been implemented to monitor the content and provide a basis to distinguish between good and poor quality knowledge assets. This paper proposes a model to uncover the role of trust in expert and peer reviews during the knowledge application process by considering its antecedents, its outcomes, and the influence of perceived risk. The model suggests that trust in expert and peer reviews is based on the ability, benevolence, and integrity of the respective group and is positively influenced by a higher trustor's propensity to trust. Perceived risk in a particular situation influences the decision whether to apply knowledge based on trust in expert or in peer reviews. It is assumed that high-risk decisions are based on expert reviews more likely because the organizational and individual risk is perceived to be lowered, whereas peer reviews can only mitigate organizational risk.

Keywords: Trust, Perceived risk, Knowledge application, Review mechanisms.

1 Introduction

Knowledge management systems (KMS) have been designed to support knowledge creation, storage/retrieval, transfer, and knowledge application in organizations (Alavi and Leidner, 2001). The first three processes are necessary but not sufficient to gain competitive advantages: an enhancement of organizational performance only arises from an effective knowledge application (Grant, 1996). Given the importance of knowledge application, research has found a surprisingly huge gap between accumulated knowledge in electronic repositories and its re-use (Davenport et al., 2003; Desouza, 2003). In the search for an explanation, several barriers can be identified which prevent organization members from applying this knowledge including distrust in the knowledge source and risk aversion of knowledge recipients (Davenport and Pruzak, 1998).

Trust is identified as the most important factor to overcome these barriers and thereby to contribute to a more efficient knowledge management (Davenport and Pruzak, 1998). Addressing the issue of distrusting knowledge sources, source credibility has been modeled to directly influence knowledge application (also described as information adoption or knowledge re-use) in recent research on electronic knowledge repositories (Boh, 2008; Zhang and Watts, 2008). However, both studies develop their hypotheses under the premise that source credibility can be clearly assessed by knowledge recipients. This assumption must be adjusted at least since the success of social media has entailed an increasing use of user-generated knowledge in organizations (which is referred to as Enterprise 2.0 (McAfee, 2006)). Assets from user-generated knowledge repositories cannot, or can only with considerable effort, be attributed to a specific origin (Jarvenpaa and Majchrzak, 2010). On the one hand, the number of potential sources (and thus also potential unknown sources) rises rapidly when enabling all organizational members to contribute and, on the other hand, knowledge assets can be altered incrementally by various sources (cf. Metzger, 2007).

KMSs must be designed in a way that knowledge workers are able to rapidly identify high-quality content (Thomas et al., 2001) without being overburdened by the evaluation of source credibility. A more efficient approach to evaluate knowledge assets than relying solely on the ability, time, and desire of organization members to scrutinize change logs or user profiles can be seen in review mechanisms (Kayhan et al., 2013; Poston and Speier, 2005). Due to the favorable role of trust in knowledge management, these mechanisms can only foster knowledge application if they are executed by trustworthy institutions. In view of the fact that many attempts to set up trust enhancing components fail (Leimeister et al., 2005), it is important to understand the dynamics of trust in review mechanisms within KMSs starting with antecedents of trust and ending with the effect of trust on knowledge application.

Apart from the consideration of antecedents and outcomes of trust, it is important to take into account that trust cannot be detached from situational characteristics (Gefen and Pavlou, 2006). Whereas uncertainty regarding the source and the quality of content can be controlled via review mechanisms, contextual factors that are linked to knowledge application (e.g., risk) are exogenous. Identifying risk aversion as one of the biggest obstacles to knowledge application (Davenport and Pruzak, 1998) implies that knowledge recipients weigh potential positive or negative outcomes of applying the knowledge before the actual behavior. Thus, perceived risk should be considered when modeling knowledge application.

Although review mechanisms have been already deployed in user-generated knowledge repositories (Bughin et al., 2008), little is known about the underlying effects of knowledge application based on trust in these mechanisms. Uncovering both the factors determining the trustworthiness of review mechanisms and the influence of risk on the choice of a reviewing institution can help to overcome the barriers to knowledge application and to bridge the gap between existing knowledge and its re-use. Therefore, the objective of this paper is to provide an integrated examination capturing the role of trust in review mechanisms within KMSs in the knowledge application process. The following research questions are addressed in particular: (1) which factors influence trust in review mechanisms in KMSs? (2) How does perceived risk influence the decision whether to apply knowledge based on trust in expert reviews or peer reviews?

The paper is organized as follows: in the next section the hypotheses are developed on the basis of extant literature on trust in KMSs and trust in the online environment. This section introduces the factors influencing trust in review mechanisms and addresses the role of risk during the knowledge application process. The following section discusses the research method by describing the study design and the measurement. In the last section, the paper is concluded with a discussion about the expected contributions.

2 Theoretical Development

2.1 Drivers of trust in review mechanisms

An integrative framework to explain trust, its antecedents, and its outcomes in organizations by considering the role of context (especially risk) as well as characteristics of the trustor and the trustee was developed by Mayer et al. (1995). Ability, benevolence, and integrity are identified as constituent parts of trustworthiness in organizational settings on the basis of an extensive literature review. Ability describes problem solving competencies within a specific area. Benevolence addresses the motivation of the trustee to help a trustor without considering potential personal benefits. The perception that the trustee follows a similar set of social rules and principles as the trustor is called integrity. The model suggests that if a trustor perceives the trustee's trustworthiness to be sufficient, it results in trust toward the trustee. However, this trust will only be followed by an action (e.g., knowledge application) if the level of trust surpasses the risk perceived in a situation. From this, the following definition of trust is derived: trust is "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995). When transferred to the current research, this means that knowledge recipients trust in the review mechanisms in KMSs and implicitly accept the risk that potential negative outcomes are inherent when applying knowledge.

In contrast to situations where the trustee is clearly identifiable, the perceived trustworthiness of intangible and faceless online information made by multiple authors can hardly be described using each of the human characteristics ability, benevolence, and integrity. In KMSs, knowledge recipients are confronted with multimedia (e.g., text, numbers, images) instead of persons. Where no context is given, the question can be raised whether one should trust client-based, website-based, or organizational antecedents of trust in an online environment (Beldad et al., 2010). However, the consideration of each of the potential trustees and trusted objects might lead to different perceptions of trustworthiness. Trusting a third party which has evaluated the content can serve as an alternative and more efficient approach for knowledge recipients since judging the trustworthiness on the basis of other's evaluations requires less cognitive effort than elaborating all possible cues in the decision-making process (e.g., change logs or user profiles). In personal relationships one might ask a colleague if s/he knows whom to trust when facing new or unfamiliar knowledge that cannot be evaluated with one's ability (Jøsang et al., 2007) – the analogs in KMSs are trust signals from reviewing institutions. In contrast to information in knowledge repositories itself, ability, benevolence, and integrity may well be attributed to identifiable intermediaries. Figure 1 summarizes the concept of mediated trust introduced in this section.

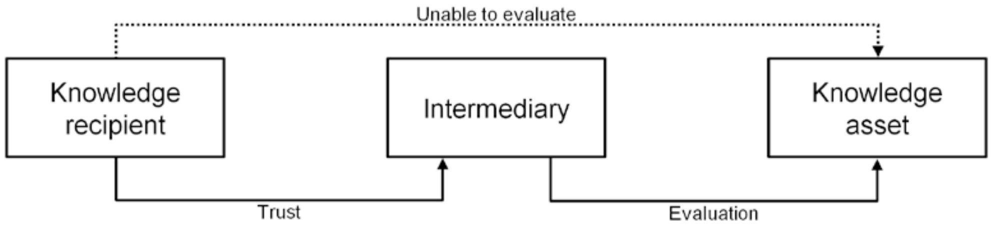

Figure 1. Mediated trust

On the Internet, an evaluation of content on a website can be executed by two different entities: users and experts. In the context of e-commerce, user reviews indicate others' opinions of the quality of products or services. Third parties are requested to put a seal on a website as part of trust-building strategies (Kimery and McCord, 2002) and they are expected to have a positive effect on the expectations of consumers toward online transactions (Kovar et al., 2000). A similar distinction can be made within organizations where fellow users become peers and third party endorsements are represented by hierarchically legitimated experts who evaluate user-generated content in KMSs (Kayhan et al., 2013).

The ability of the trusted party to evaluate information accurately is hypothesized to be an important antecedent of trust (Mayer et al., 1995). Evaluation of content has no value for knowledge recipients in case the trustee is not knowledgeable in the particular field. Along with this, French and Raven (1959) state that, when ability is given, it is necessary to be sure that trustees act according to their best of knowledge and belief. Transferred to online reviews in KMSs, this means that trustors should be able to rely on the benevolence of experts or peers to build trust. Integrity as the third part is also assumed to be very important in the context of trust in expert and peer reviews. In absence of similar organizational values and an identical understanding of information quality, trusting in a review can be unintentionally counterproductive (Jarvenpaa and Majchrzak, 2010). Since all of the mentioned components lead to a higher trust as a part of perceived trustworthiness, it can be hypothesized:

Hypothesis 1: A higher perceived trustworthiness of experts consisting of (a) ability, (b) benevolence, and (c) integrity will positively influence the trust in expert reviews.

Hypothesis 2: A higher perceived trustworthiness of peers consisting of (a) ability, (b) benevolence, and (c) integrity will positively influence the trust in peer reviews.

In a dyadic relationship both the trustee's and the trustor's characteristics should be borne in mind. In accordance with the assumption of Mayer et al. (1995) that the individual propensity to trust in an organizational setting influences the transition from perceived trustworthiness to trust, a higher general propensity to trust is embodying a higher level of trust in the evaluation of experts and peers in KMSs. People might vary in their willingness to trust due to different cultural backgrounds (Hofstede et al., 1991; Vance et al., 2008). Even within cultural areas this trait might differ depending on the organizational information culture (Davenport and Pruzak, 1998). Nevertheless, it can be assumed that a higher propensity to trust leads to an enhancement of the positive effect of trustworthiness signals on trust.

Hypothesis 3: A higher propensity to trust has a positive moderating effect on the relationship between (a) ability, (b) benevolence, and (c) integrity and trust in expert reviews.

Hypothesis 4: A higher propensity to trust has a positive moderating effect on the relationship between (a) ability, (b) benevolence, and (c) integrity and trust in peer reviews.

2.2 Knowledge application based on trust in review mechanisms

Chaiken (1980) suggests that heuristic processing results in people relying on general rules which were developed during experiences and observations in their past. Potential rules are, for example, that experts are generally credible or that a consensus of a group of people can be trusted. Unlike technology-based peripheral cues, trust in experts and peers can also be attributed to different manifestations of social power. French and Raven (1959) identify five bases of power which can be applied in this context: expert power, legitimate power, referent power, reward power, and coercive power.

Trust in expert reviews can be primarily associated with expert power which is caused by the skills of an expert in a specific situation. A demonstration of expertise is required to trust in the knowledge source. In organizations which anchor expert review systems in their hierarchical structure, legitimate power is conceivable as an additional mechanism. Legitimate power describes the power derived from a formal authority within a social or organizational structure. In this context both powers can cause knowledge recipients to perform an action based on trust in expert reviews. A combination of reward and coercive power can occur when experts are equipped with the rights to reward applications of the expert review or to punish misuse. Empirical studies have shown that sources of feedback with a high expertise have a higher effect on the behavior of the knowledge recipients than low expertise sources (Barnett White, 2005; Brown et al., 2007).

Hypothesis 5: A high level of trust in expert reviews has a positive effect on knowledge application.

The influence of peer reviews on behavior can be linked to referent and expert power. Referent power describes the phenomenon that individuals tend to be closely associated and hold similar opinions with reference groups and persons to attain satisfaction by conformity. A second mechanism which underlies a behavior based on trust in peer reviews can be assumed when conformity based on identification is not the trigger of the behavior. French and Raven (1959) argue that conformity with a group opinion can also be caused by expert power. For this, the knowledge recipient must perceive aggregated wisdom as a form of expertise. Since peers represent a powerful social system within organizations, reviews based on their elaboration are likely to influence the desire to conform with the group (Angst and Agarwal, 2004).

Hypothesis 6: A high level of trust in peer reviews has a positive effect on knowledge application.

Previous studies which consider trust as a driver for different behavioral outcomes such as software usage or information contribution and retrieval (e.g., Gefen et al., 2003; Kügler et al., 2012; Ridings et al., 2002) almost exclusively simplify the effect of trust on behavioral outcomes by assuming a linear relationship between both variables and not considering contextual factors (cf. Gefen et al., 2008). However, Gefen and Pavlou (2006) have shown that situational characteristics can moderate the impact of trust on behavioral outcomes. Therefore, different behavioral outcomes of trust may occur due to contextual factors that cause trustors to feel vulnerable (Gefen et al., 2008), even if the level of trust based on ability, benevolence, and integrity is constant. The consideration of context includes predicting the potential positive or negative consequences (perceived risk) of the behavioral outcomes of trust in review mechanisms (Coleman, 1994). In the context of this research, perceived risk refers to the potential positive or negative outcomes of knowledge application. For example, applying new instructions on how to calculate a key performance indicator from an user-generated knowledge repository may lead to faster processes (positive outcomes) or to a miscalculation of the indicator and misguided subsequent decisions (negative outcomes). If the knowledge recipient is embedded in an organizational structure, the perceived risk of applying knowledge from KMSs can consist of an organizational risk (e.g., financial loss, performance loss) and an individual risk (e.g., social loss, job loss) (Jacoby and Kaplan, 1972; Lazo, 1960; Mitchell, 1995; Roselius, 1971).

A rational choice would be to trust the third party which promises the lowest potential negative outcomes (Friedman et al., 2000). Since the perceived organizational risk remains constant on condition that both experts and peers are perceived equally trustworthy, reducing the perceived individual risk is left as a mechanism to enhance the relationship between trust in intermedaries and knowledge application. While reviews of peers offer no guarantee, experts with a legitimated power can efficiently achieve this aim within an organization since knowledge recipients can regard expert reviews as implicit work instructions and must assume that the information is in accordance with organizational values. A misguided action on the basis of erroneous expert reviews can be assigned to higher hierarchical levels instead of the individual who applied poor quality knowledge. This sense of safety provided by expert reviews can lead to basing the application of knowledge on expert reviews rather than peer reviews in situations with a high perceived risk.

Hypothesis 7: A higher perceived risk has a positive moderating effect on the relationship between trust in expert reviews and knowledge application.

Hypothesis 8: A higher perceived risk has a negative moderating effect on the relationship between trust in peer reviews and knowledge application.

2.3 Control variables

The presented research model is aiming to uncover one important facet of the knowledge application process in detail. Several factors that have been shown to influence the dependent variable and moderate the path between trust intermediaries and knowledge application in previous research were intentionally omitted from the model for clarity. Nevertheless, they must be controlled for their influence to get a comprehensive view.

Research across various technologies and settings has found information quality to be the most important predictor of knowledge application (e.g., Bhattacherjee and Sanford, 2006; Sussman and Siegal, 2003). Since the quality of the presented information comprises objective and subjective dimensions (Lee et al., 2002), the perceived information quality of identical knowledge assets may differ from person to person. Therefore, it will be controlled for its influence on knowledge application.

Whereas perceived information quality is assumed to influence the dependent variable directly, the knowledge user's elaboration likelihood of the knowledge asset will be controlled for its moderating effect on the relationship between trust in intermediaries (peripheral cues) and knowledge application. Elaboration likelihood captures relevant expertise and involvement of the knowledge recipient following Sussman and Siegal (2003).

Figure 2 provides an overview of the variables and relationships of interest and shows the research model.

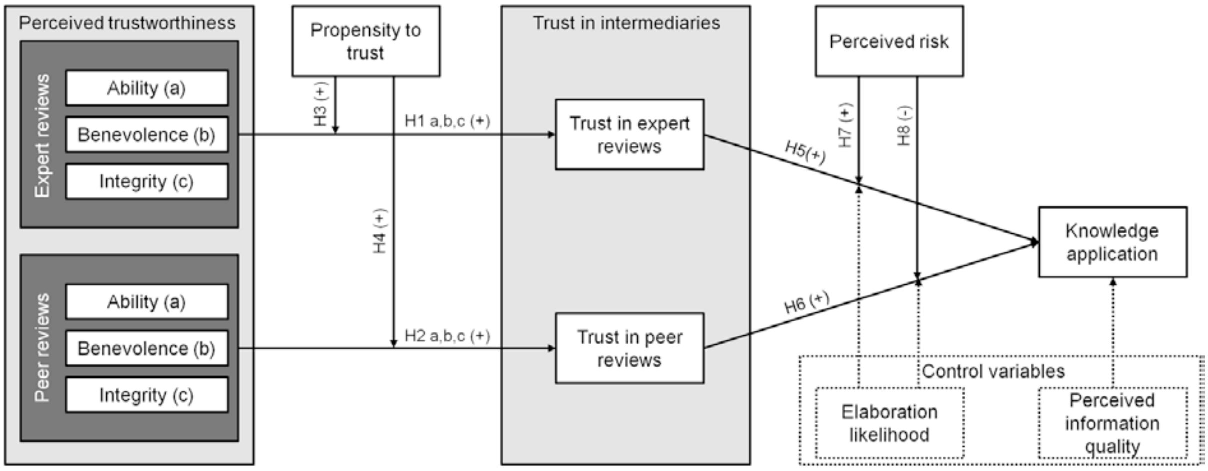

Figure 2. Research model

3 Research Methodology

3.1 Study design

In order to test the proposed research model, two independent experimental studies will be conducted. First, the study design including measurement models and distinctness of manipulations will be tested by an exploratory study using a student sample. Second, the final study will be conducted targeting knowledge workers within an organization to enhance the external validity.

Since manipulating real data could have serious consequences and a situation should be created where no relationships exist between the knowledge source and knowledge recipients (which could affect the results in an undesired way), a 2x2x2 factorial experiment will be employed. A factorial design is well suited to test this research model since it is more efficient than one-factor-at-a-time experiments, effects of the independent variables are tested at different levels of the other factors, and unanticipated interaction effects can be detected to avoid misinterpretations (Montgomery, 2008).

Mockups of a user-generated knowledge asset have been built with all combinations that arise from displaying and hiding favorable expert and peer reviews. The fictitious knowledge asset contains a comparison of an official instruction and an alternative proposal which is supported by the knowledge source. Both approaches remain ambiguous (there is no wrong or right approach) since trust is especially relevant for uncertain situations (Gambetta, 2000). Participants will be asked to solve a task based on the displayed knowledge asset. Thereby, solving the task based on the supported approach will be regarded as knowledge application.The risk manipulation will be described in the introduction and is conducted as follows: under the high risk condition, participants will be promised a prize for the correct answer. In addition, it will be announced that names of participants with a wrong answer will be disclosed after the study. Both stimuli address individual risk. Additionally, it is stated that every incorrect answer reduces the total prize volume to address organizational risk. Under the low risk condition, no prizes or punishments are announced.

The schedule of the studies will be set up as follows: (1) an invitation mail will be sent out to participants including a task to evaluate a user-generated knowledge asset (which is actually unrelated to the study) on the universities' web-based learning platform /in a corporate KMS on a 5-star rating scale in a brief web-based survey. (2) On the day of the experiment, groups of students/employees will be seated in front of computer terminals. One of the eight scenarios will be randomly assigned to each participant. An introduction (low /high risk) will be shown followed by the knowledge asset and the task. Authentic institutions will be employed as expert reviewers (professor /department head). Peer reviews are announced as the results of the knowledge asset evaluation included in the invitation mail from another group of students/employees (a high rating will be used instead of measured data). (3) After solving the task, participants are requested to fill out a questionnaire containing items which cover the constructs summarized in figure 1. (4) Since there are no correct answers to the task, names will not be disclosed and prizes will be raffled among participants.

3.2 Measurement and data analysis

The empirical investigation of the research model requires an operationalization of the constructs using appropriate measurement models. Apart from the choice of suitable items, the direction of relationships in the measurement model has to be considered (reflective or formative). Established and reliable instruments were drawn from prior research and tailored to the specific research context. The scales of ability, benevolence, integrity, and propensity to trust are taken from Gefen and Straub (2004). Trust in expert and peer reviews will be measured using items from Gefen (2000). Risk will not be calculated using the dichotomous manipulation variable (high risk /low risk). Instead, it will be measured separately to address differences in the perception of risk. In line with the definition of perceived risk in this paper, organizational risk and individual risk will be taken into account by applying a formative measurement model to capture the two aspects of the construct (Petter et al., 2007). For this, items concerning organizational risk are drawn from Houghton et al. (2000) and the items of individual risk are taken from Featherman and Pavlou (2003). The measurement items regarding the control variables perceived information quality, expertise, and involvement are adopted from Sussman and Siegal (2003). All items will be measured using a seven-point Likert scale with the anchors being "strongly disagree" and "strongly agree". The manipulations will be captured by dummy-coded dichotomous variables using 0 for no expert review /peer review and 1 for a displayed expert review /peer review.

Data collected during the experiments will be computed using partial least squares (PLS). This method is chosen to test the presented research model because of four advantages compared with traditional (co)variance-based approaches (e.g., AN(C)OVA): measurement errors can be controlled, PLS is less demanding regarding the sample size and distributional characteristics, reflective and formative indicators can be considered simultaneously, and it can handle complex research models (Streukens et al., 2010). The measurement model will be validated following the guidelines from Straub et al. (2004). After initial manipulation checks, a two-step approach will be applied to validate the structural model. First, the direct effects will be computed and second, moderating effects will be included in the calculation.

4 Conclusion

The present work is aiming to uncover the role of trust in expert and peer reviews during the knowledge application process in KMSs by considering its antecedents, its outcomes, and the influence of perceived risk. Two major questions remain unanswered in existing literature: (1) which factors influence trust in review mechanisms in organizational electronic knowledge repositories? (2)

How does perceived risk influence the decision whether to apply knowledge based on trust in expert reviews or peer reviews? To answer these questions an integrative model was developed which suggests that trust in expert and peer reviews is based on the perceived trustworthiness (ability, benevolence, and integrity) of the respective group and is positively influenced by a greater trustor's propensity to trust. Perceived risk in a particular situation influences the decision whether to apply knowledge based on trust in expert reviews or in peer reviews. It is assumed that high risk decisions are based on expert reviews more likely because organizational (e.g., financial loss) and individual risk (e.g., social loss, job loss) are perceived to be lowered, whereas peer reviews can only mitigate organizational risk.

Bridging the mentioned research gaps can contribute to both the theoretical and the practical field. By separating trustworthiness and trust, and considering perceived risk as a moderating variable, the study seeks to develop an understanding for underlying effects of how trust in reviews functions and how situational characteristics influence the effect of trust on behavioral outcomes. With this approach, the need for a closer examination of knowledge application under the premise of not knowing the knowledge origin (Alavi and Leidner, 2001) and the call to examine the dimensionality of trustworthiness and the influence of context on trust (Gefen et al., 2008) are addressed.

In the practical field, the results of this study can have tangible implications for design and management of KMSs in organizations. Potential differences between the effects of ability, benevolence, and integrity on trust in intermediaries regarding their strength can serve as guidance for the setup of peer and expert review mechanisms and their concrete representation. Those review mechanisms in turn can be deployed for certain fields of knowledge or individual knowledge assets depending on the potential risk of applying knowledge from these sources. In summary, this study will provide the basis to establish an efficient review-content-fit.

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Essay II

Titel

Towards a Social Data Enriched Search Algorithm for Business Intelligence Portals

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Towards a Social Data Enriched Search Algorithm for Business Intelligence Portals

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Abstract: Today's knowledge workers are confronted with a vast amount of data. Information overload foils them from finding relevant information. This especially is a problem in Business Intelligence (BI) portals where data sources differ, data is multi-structured and many reports may look similar despite providing different insights. Therefore, most BI portals offer their users simple search functionalities based on algorithms that solely take into account a report's metadata to calculate the extent to which it matches a user's search query.

However, the ongoing integration of Web 2.0 features in corporate software is leading to a pool of social data that can enrich this calculation. More precisely, incorporating personal data about the user entering the search query (such as age or hierarchical position) can help matching search results and individual information needs. In addition, data about other users' interaction with available reports (e. g., usage histories) can be considered for ranking search results and may improve search quality.

The potential of integrating social data has long been recognized due to the implementation of web search algorithms. We argue, however, that these algorithms should not simply be transferred to BI portals since they do not consider the specificities of the data available in this context. Therefore, there is a research gap between the users' need for social search functionalities and existing BI software.

In this research-in-progress, we address this gap and take a first step towards designing an algorithm optimized for a social BI search. More precisely, we identify the data variables available in common BI portals, classify each variable by whether it is report-related, user-related or interaction-related and argue how we expect it to influence the relevance of a report to a user. This classification serves as the basis to develop a search algorithm for the use on BI portals as the next logical step.

Keywords: Business Intelligence, search algorithm, knowledge management, social data, search engine

1. Introduction and background

The vendors of Business Intelligence (BI) software face new challenges triggered by current technical and organisational BI trends: For example, big data and social media analytics are two dominant technical trends that cause requirements which go beyond the potentials of traditional systems on the intranet. Additionally, the lifting of access restrictions as an organisational trend leads to an increasing number of BI users with low analytical skills. As a consequence of both trend types, users as well as vendors are confronted with a growing amount of data and reports within enterprises. Existing BI portal solutions do not match the demands regarding an efficient information search in this new intranet environment (Böhringer et al. 2009).

An intranet search solution aims to find all knowledge assets within the corporate intranet that relate to a user's search query. Intuitive and efficient approaches to search a large amount of data are known from the internet (e.g., google.com). Furthermore, web-search-like graphical user interfaces require no additional training effort for knowledge workers (Evelson 2012). However, we argue that a simple porting of web search algorithms leads to an insufficient quality of search results on the intranet due to the following specificities:

- often only one correct result,
- more detailed social data available,
- identification of users across system boundaries,
- well structured objects,
- higher risks when adopting information,
- no search engine optimization,
- lower variety of search inputs,
- lower amount of "junk" data,

- no links to rank results.

Although intranet search engines are embedded in an environment of lower complexity, their quality is perceived to be lower than the quality of their internet counterparts (McAfee 2006). The importance of a useful search engine on the intranet can be seen by the fact that three out of six constituting technology characteristics of Web 2.0 technologies in enterprises (search, links, and tags) can directly be linked to search (McAfee 2006). However, links are often not available and, therefore, other cues have to be taken into account (Chaudhuri, Dayal & Narasayya 2011). One possible cue can be the integration of social data, a strategy that has been proven to be successful in a web search context (e.g., Google integrated data from its social network Google+ into its search functionality in an upgrade called “Search plus Your World”, (Singhal 2012)). Indeed, there have been approaches to integrate data from social media into intranet search (e. g., Ronen et al. 2009). Contrarily, little work has been done to enrich BI search with social data. BI search basically works similar to intranet search, but its scope is usually restricted to reports created within a BI platform. Thereby, it can exploit the (meta)data specific to this asset type (e.g., the usage of filters) and the social data related to them (e.g., how many users have searched for reports containing a certain filter). Since the contribution of social data is voluntary, we do not expect any data privacy concerns.

In section 2 of this paper, we identify variables whose consideration for BI search can improve the ranking of search results. In section 3, we conclude our work and discuss how we intend to proceed.

2. Variables

According to Inmon, O’Neil and Fryman (2008) the variables taken into account to assess a report’s relevance can be distinguished in variables that are common in all document types (e.g., creation date) and variables that can be used to classify a document (e.g., tags, keywords, etc.). Both variable types are substantial parts of a report but not of a user. Thus, when incorporating social data into BI search, this dichotomy becomes insufficient. Therefore, we suggest a categorisation of search relevant variables into the following categories:

- *Report-related variables*: data of the report and metadata describing its content.
- *User-related variables*: accessible information about the user itself drawn from the roles and functions management and the user’s report usage history and search history.
- *Interaction-related variables*: information attributed to a report by its users and the observed data of other users’ interaction with the report.

As mentioned before, the traditionally most important variables when estimating the relevance of a report to the querying user are those who describe the report’s content. They primarily comprise the report’s title, its (short) description, some tags, its structure (i.e., filters, rows, columns, etc.) and the concrete data it is based on. Typically, except the latter, all of these variables were set by the author of the report at creation time. However, after the integration of social data in our analysis, we are also able to observe with which queries the other users who have seen the report have searched, constituting a form of social annotations. Furthermore, the report might have been commented, rated or tagged by those users. This additional information can also be searched through (Dmitriev et al. 2006). All those descriptive variables can be considered in a similar way: The degree to which they match a user’s search query determines the report’s estimated relevance to the information seeking user.

The second major source of information we can exploit when integrating social data are the relationships between users (Carmel et al. 2009). For this purpose, we observe for each user his role in the system and in the organization. Since we are aware of the organisational structure that is reflected by the roles and functions management integrated in the BI system, we can evaluate the relations between these positions in hierarchies. For example, if we know that a report has been relevant to a colleague of the querying user (i.e., to a user on the same hierarchical level), this knowledge increases the probability that the report will also be relevant to this user itself.

Of course, a report’s relevance to other users is not known ex ante. However, it can be inferred by the observable behaviour of these users: Their search histories tell us in which topics they have been interested; then, factoring in the usage statistics of each report, we can guess whether they have found what they have looked for (indicating a high relevance of the report) or not (indicating a lower relevance). Furthermore, other users might have rated, commented, shared or updated the report, which information also can be used to estimate its relevance to them.

The relationships between users themselves can be moderated by many observable variables. If we know how often the querying user interacts with other users (defining his "network"), we can use this information to weight the corresponding relationships accordingly. A set of further variables that can be exploited for this purpose are the querying user's personal characteristics in relation to the report's features. If, for example, the report is presented in a language that the querying user does not understand, it can be assumed to be of low relevance to him, despite having been relevant to a colleague who is able to speak this language.

Finally, there are some variables which influence the meaning of other variables. For example, a report's creation date should be considered as a way to normalize its usage statistics in order to allow a fair comparison with other reports of a different age.

In Figure 1, we provide an overview over the most important variables that can be taken into account in at least one of the ways described above. Each variable is classified according to whether it is report-, user- or interaction-related. In addition, we distinguish for each variable whether it influences a report's objective (to all users) or subjective (to the querying user) relevance, constituting a further dichotomy.

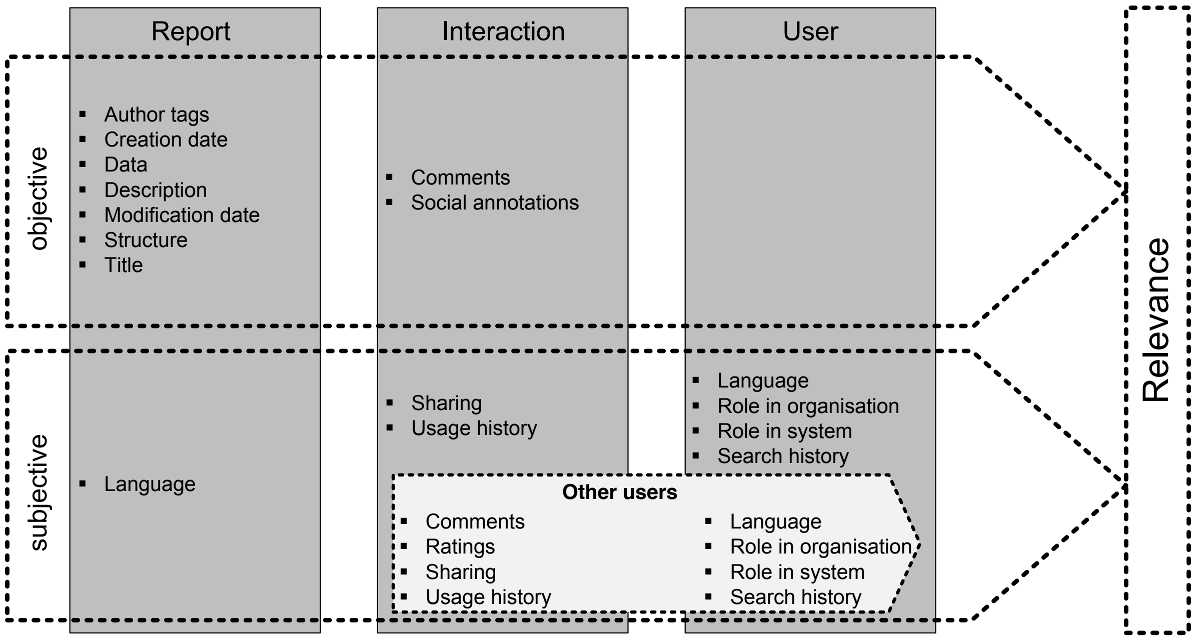

Figure 1: Classification of variables for BI search

3. Conclusion and further research

In this paper, we have identified variables that have to be considered when developing a search algorithm for BI portals. Furthermore, we have classified them in accordance to their character into report-related, user-related and interaction-related variables and distinguished whether they influence a report's relevance objectively or subjectively.

Based on this classification, we aim to develop a search algorithm for BI portals and evaluate it by implementing it in a testing environment following the design science paradigm (see Hevner et al. 2004). The completed research will not only contribute to theory but also have tangible implications for technology-oriented and management-oriented practitioners.

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Essay III

Titel

Influence of Social Software Features on the Reuse of Business Intelligence Reports

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Influence of social software features on the reuse of Business Intelligence reports

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ABSTRACT

Vendors of Business Intelligence (BI) software have recently started extending their systems by features from social software. The generated reports may include profiles of report authors and later be supplemented by information about users who accessed the report, user evaluations of the report, or other social cues. With these features, users can support each other in discovering and filtering valuable information in the context of BI. Users who consider reusing an existing report that was not designed by or for them can now not only peruse the report content but also take the social cues into consideration. We analyze which report features influence their perception of report usefulness. Our analysis is based on the elaboration likelihood model (ELM) which assumes that information recipients are either influenced by the quality of information or peripheral cues. We conduct an experiment with knowledge workers from different companies. The results confirm most hypotheses derived from ELM in the context of BI reports but we also find a deviation from the basic ELM expectations. We find that even people who are able and motivated to scrutinize the report content use community cues to decide on report usefulness in addition to report quality considerations.

1. Introduction

Knowledge is a company's most important resource in today's knowledge-based economy (Grant, 1997; Nickerson & Zenger, 2004). While each employee possesses knowledge individually, it is the primary task of the company to manage all available knowledge and to integrate it into products and services (Grant, 1996). Therefore, firms aim to implement effective knowledge management (KM) processes including knowledge creation, capture, distribution, and reuse (Alavi & Leidner, 2001). The first three processes form the basis of KM, whereas the effective reuse of existing knowledge assets can help to gain competitive advantage (Davenport & Prusak, 2000) because it helps to prevent employees from re-creating redundant knowledge and thereby saves time and money (Akgün, Byrne, Keskin, Lynn, & Imamoglu, 2005). Knowledge does not refer only to a single chunk of knowledge but can also refer to complex digital assets such as program code, system design information, an instruction manual, the description of a case and its solution, or a report. Probably the most studied type of

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knowledge reuse in the context of information systems (IS) is software reuse (Frakes & Fox, 1995). Three phases can be distinguished in knowledge reuse:

(1) Retrieval of potentially relevant knowledge.
(2) Evaluation of knowledge usefulness for the task at hand.
(3) Actual use incl. possible adaptations, if the knowledge was considered useful.

Phase 1 has been studied extensively and phase 3 has also received some attention (e.g., in case-based reasoning (Aamodt & Plaza, 1994). The second phase did not receive much attention; it is usually implicitly included in phase 1. However, human decision makers do not all interpret the facts and signals they receive in the same way. They often perceive them differently or pay attention to a different subset of signals. Therefore, we concentrate on the second phase to better understand whether and which facts and signals may influence their decision on reuse.

One important part of an effective knowledge management is Business Intelligence (BI) (Gold, Malhotra, & Segars, 2001) which is defined as a "strategic approach, for systematically targeting, tracking, communicating and transforming relevant weak signs into actionable information on which strategic decision-making is based" (Rouibah & Ould-ali, 2002). It includes the generation and distribution of reusable reports as well as statistical and mathematical analyses (e.g., data mining). In the early days of electronic data processing, reports have been developed by programmers based on user specifications. Nowadays, knowledge workers have been empowered to create reports by themselves which is called self-service BI (SSBI) (Evelson, 2012). Self-service BI is supported by user-friendly tools and an increasing amount of data and new data sources which enable knowledge workers to perform more detailed analyses than previously possible (McAfee & Brynjolfsson, 2012). In addition to strategic and tactical analyses, which are standard tasks of BI systems, operational analyses are increasingly performed (Böhringer, Gluchowski, Kurze, & Schieder, 2009). More granular and current data are available for this purpose, while new and often inexperienced user groups are trying to use the technology. In this situation, organizations have to find ways to disseminate new information more effectively (Bevanda & Pavletić, 2007) and to increase its reuse. How important this issue may become show the figures reported in Eckerson (2008). An energy company found after a few years of adopting SSBI 26,000 reports stored by only one department. This huge amount of reports precluded people from using them rather than attracting them. After perusal of the reports, the number was cut down to 300 reports containing almost the same information. This indicates that with better reuse the growth of the number of (possibly redundant) reports would not have been so dramatic.

Therefore, we study the cognitive preconditions of reuse of previously created reports. People will use them if they find them useful to (partly) satisfy their information needs. Reuse of a report may mean the use of a report as it is, the application of the same reporting procedures to another data set (e.g., a report designed for country A is executed on the data of country B), or an adaptation of the report to include, for example, an additional calculation. Of course, combinations of the latter two adaptations are also possible, i.e., a change of the data set and calculations.

Another advancement of the last years is the rise of Web 2.0 or social media (O'Reilly, 2007). First, they became popular in the private realm but meanwhile they have entered the corporate world where they are supporting the move toward Enterprise 2.0 (McAfee, 2006). This integration of social software tools in corporate intranets offers one possible solution to the challenge of targeted report dissemination and reuse. BI reports can be enriched by social software features such as tagging, rating, information on frequency of use, comments, and information on the identity of the report author or other report users. This is possible if report creators make their reports available on a BI portal so that information on their use by other users can be added over time, partly automatically (e.g., frequency of use). Software vendors like SAP (SAP StreamWork, 2013), IBM (IBM Connections, 2013), and Microsoft (Microsoft SharePoint, 2013) have already expanded their BI portals to incorporate some of the mentioned features. From a research perspective, Meredith and O'Donnell (2010) present a mock-up of an analysis tool with social media functionality while Böhringer et al. (2009) describe a design prototype which integrates social aspects in a BI portal (see Fig. 1).

However, these prototypes are based on conceptual thinking and the suggested features were not tested regarding their influence on report reuse. Thus, our study aims to examine if the enrichment of BI reports by social software features influences their reuse and to reveal the underlying patterns of the influence processes.

The most commonly used theory to examine influence processes in IS research is the elaboration likelihood model (ELM). ELM studies how people form and change attitudes based on the information they receive. Perceived usefulness of an IS or a report is such an attitude. Perceived usefulness of an IS artifact can be defined as the degree to which people believe that the use of this artifact would improve their working performance (Davis, Bagozzi, & Warshaw, 1989). ELM distinguishes two persuasion processes by the type of information processed and explains under which circumstances an information recipient might be more influenced by one process or the other (Petty & Cacioppo, 1986). Utilizing ELM to address the above mentioned research gap can help us to answer the following research questions in particular:

(1) Which social software features influence the perceived usefulness of reports designed by other people?
(2) Are these influences moderated by job-related characteristics of the report user and if so, how?

Answering the two questions is both theoretically and practically important. On the one hand, we advance theoretical knowledge by examining the role and nature of influence processes of social software features in a software environment

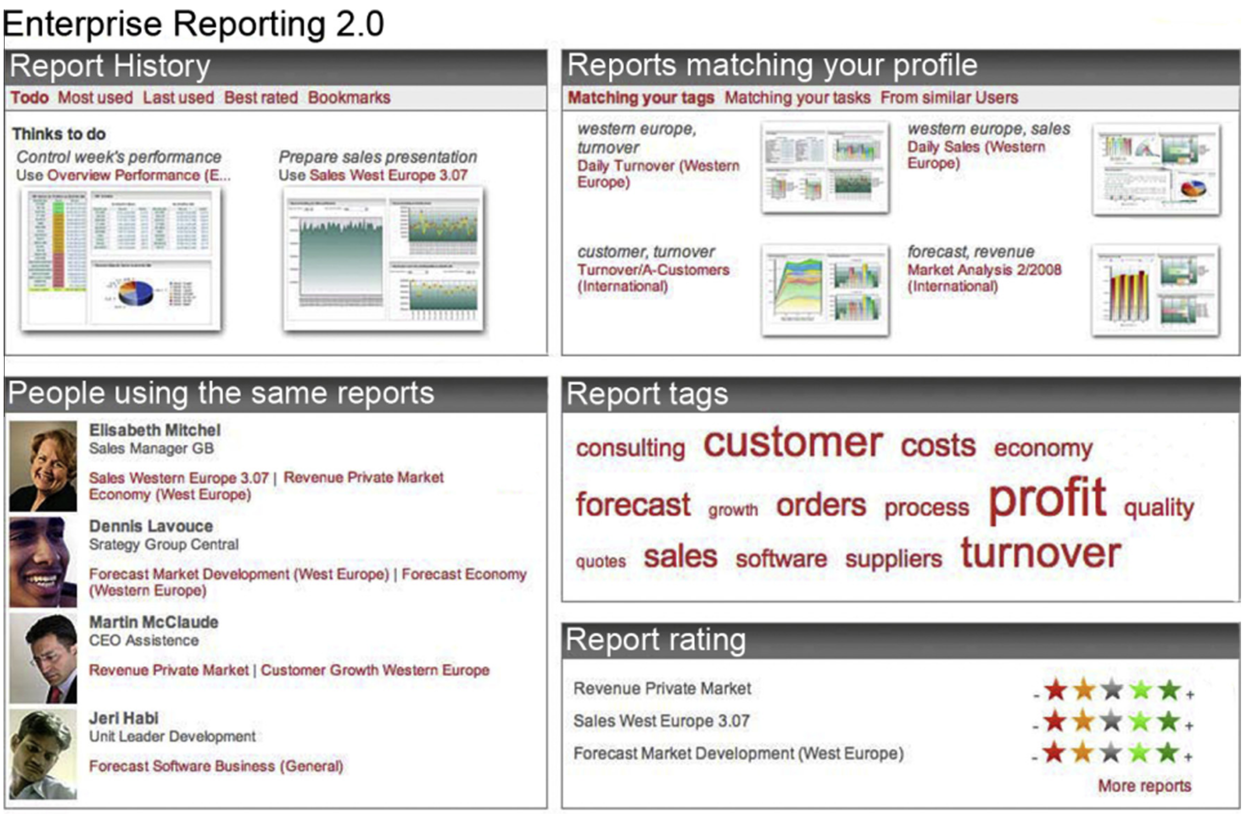


Fig. 1. Prototype which integrates social aspects in a BI portal, adapted from Böhringer et al. (2009).

initially designed to present purely objective data. On the other hand, the study can help practitioners to adjust the implementation of these features in order to fit the company's BI user's needs.

The paper is organized as follows: first, we provide the conceptual background and give an overview of previous applications of ELM in the IS context. Second, we describe the core factors of this study and derive the hypotheses. Then, the research model is empirically tested using data from an experiment with knowledge workers who regularly receive or generate BI reports. We end with a discussion of the study's results and practical implications.

2. Background

2.1. Theoretical background

A combination of two major research streams provides the theoretical foundations for our study. On the one hand, literature on technology acceptance provides us with a strong dependent variable proven to influence behavior and, on the other hand, literature on attitude change serves as a starting point to identify factors influencing the adoption of information and variables affecting this process.

The *Technology Acceptance Model* (TAM) is an extension of the theory of reasoned action (Fishbein & Ajzen, 1975) and was introduced to assess the adoption process of IS users (Davis et al., 1989). TAM suggests that user adoption of a new technology is strongly influenced by perceived usefulness and perceived ease of use. While perceived usefulness is defined as the degree to which people believe that the use of a specific IS artifact would improve their working performance, perceived ease of use is the degree to which people believe that the use of a specific information systems artifact would be free of effort (Davis et al., 1989). These two independent variables are related to the attitude toward the technology which is itself a predictor of behavioral intention to use the technology and the actual technology use. However, TAM does not examine how perceptions on usefulness are formed or, in other words, how information is evaluated in the formation of attitudes.

Attitude change and formation is usually conceptualized using the ELM (Petty & Cacioppo, 1981, 1986). Since an extensive body of extant empirical literature found support for ELM (a detailed overview is given in the next section), we focus on this approach to develop our research model. ELM is based on the central assumption that information recipients build their attitude about given information via two different routes (central and peripheral) depending on their thoroughness of information assessment and assumes the exclusivity of either route. ELM suggests that whether information recipients take the central route or the peripheral route to form an attitude depends on their elaboration likelihood. Elaboration likelihood describes the motivation and ability to evaluate given information and elaborate the main arguments (Bhattacherjee & Sanford, 2006). In information systems research, elaboration likelihood is typically operationalized as a combination of the information recipients' expertise (reflecting ability) and job relevance (reflecting motivation) (Bhattacherjee & Sanford, 2006; Sussman & Siegal, 2003).

The first conceptual route of ELM is the so called central route. It can only be taken if an information recipient is able (e.g., because of a high expertise in this field) and motivated (e.g., because of a high personal job relevance) to scrutinize the presented information and assess the quality of the arguments included. When a recipient's expertise and job relevance are high, it is more likely that s/he is able to base their judgment on the argument's usefulness rather than relying on heuristic cues.

When elaboration likelihood is low, information recipients resort to a second route which is called the peripheral route. It encompasses peripheral cues which automatically exist (e.g., the personal characteristics of the messenger) or are purposely provided (e.g., a quality seal) in addition to the actual message or information. These cues do not necessitate a deep cognitive elaboration of the message. Neither expertise on the particular topic nor strong motivation is needed to evaluate them. The peripheral cues often represent source credibility which is commonly identified as a combination of expertise and trustworthiness of the person, originating the information (Pornpitakpan, 2004). It can be defined as the belief that the information provider is a reliable information source.

Combining these literature streams can help to gain knowledge on information influence processes which in turn can guide the design of IS to improve the reuse of knowledge assets in internal databases.

2.2. Previous research

Many articles that apply ELM in the context of IS have been published meanwhile. We identified about 70 such articles in major journals and conferences that were published in the last 16 years. They can be classified into two groups:

(1) Research that studies attitude formation (and in few cases attitude change) like in the original ELM.
(2) Studies of information influence that use the concept of perceived usefulness or a similar construct instead of attitude (see below for examples).

Since perceived usefulness is a constituent part of attitude (Rosenberg & Hovland, 1960), these studies can also be characterized as measuring the cognitive part of attitude (see discussion in Section 3). Such studies usually do not attempt to measure the general attitude of users toward a technology but to understand how they perceive or react to information received from or via the system. For example, Sussman and Siegal (2003) study the reaction of employees to advices given by co-workers via e-mail. The attitude toward e-mail is not the focus of the research although it is the underlying technology. The majority of the articles fall into this group.

Another way to classify the articles is by the organizational setting in which the technology is used (Kayhan & Bhattacherjee, 2010). The majority of the articles study information systems that are used for private purposes. In terms of e-business, these settings could be categorized as B2C or C2C settings. For example, Tam and Ho (2005) research personalization as a persuasion mechanism on web sites, Angst and Agarwal (2009) study the attitude of patients to electronic health records, and Luo, Luo, Schatzberg, et al. (2013) analyze factors of credibility of recommendations in online communities.

Here, we review articles that study information influence based on ELM within an organization, since this corresponds to our research setting. This includes studies in which the research does not take place within an organization that uses the IS under observation but the research is positioned in such a scenario. This can be the case, for example, when an experiment is carried out with student respondents. The papers are reviewed in the chronological order of their appearance.

Mak, Schmitt, and Lyytinen (1997) conduct an ELM-based experiment in the context of expert systems (ES). They use *the ambiguity of the decision setting* as the variable determining the central route of influence while *perceived credibility of the experts building the system* represents a peripheral cue. They study whether the influence of these variables on the *user decision to accept the system's advice* is moderated by *user perceived participation in knowledge update* of the ES which represents user motivation, i.e., elaboration likelihood. They determine that ELM predictions fully apply for a high level of participation in knowledge update but only partially for a low level of participation. Dijkstra (1999) also conducted several experiments with a mock-up ES using ELM. The setting in these experiments is not quite clear but we consider the work as "organizational" following the interpretation of Kayhan and Bhattacherjee (2010) and review the latest experiment here. It reveals that students with low elaboration likelihood accept wrong advices more often than those with high elaboration likelihood which also corresponds to ELM.

The influence of advices (arguments) given to a consultant by a co-worker through e-mail is studied by Sussman and Siegal (2003). They evaluate a survey of consultants from one city office of a multinational public accounting company. Each consultant answered the survey based on a self-selected e-mail. They use perceived usefulness (of advices) as the dependent variable as mentioned above. The consultants were influenced by both, argument quality and source credibility. In general, perceived argument quality can be defined as the extent to which a user of an application perceives the provided information to be complete, unambiguous, meaningful, and correct (Wand & Wang, 1996). Perceived source credibility is the degree to which people believe that the information provider is a reliable information source. The influence was significantly moderated by expertise (representing cognitive ability) and only slightly by involvement (representing motivation), the two indicators of elaboration likelihood. In addition, the effect of argument quality and source credibility on the perceived adoption of the advice is mediated by its perceived usefulness.

Angst and Agarwal (2004) combine ELM with the theories of social learning (Bandura, 1977) and social influence (Kelman, 1961). They posit that internalization influences users via the central route to commence using a system and keep using it in the long run. They expect that compliance and identification work via the peripheral route but that their influence fades over time. Their study of the use of a customer relationship management system (CRM) within a bank only partially confirms their expectations. Compliance led to an enduring, and even increasing use of the CRM. Identification also led to an increased system use via the peripheral route.

Bhattacherjee and Sanford (2006) study the intended adoption of a document management system (DMS). The authors survey personnel from a city government in a Ukrainian city. Their model combines ELM with TAM in such a way that argument quality and source credibility influence perceived usefulness which influences (affective) attitudes toward the system. Attitudes are also directly influenced by source credibility. Perceived usefulness and attitudes influence usage intentions. All main effects are confirmed as predicted by ELM and TAM. This is also true for moderating effects except in the case of job relevance, which represents motivation, where the effect on the relationships between source credibility and perceived usefulness/attitude is unexpectedly positive. The authors find an explanation for this observation, but they point out the complex nature of the construct source credibility.

Fadel, Durcikova, and Cha (2008) study information influence on the perceived usefulness in a knowledge management system (KMS) following the approach of Sussman and Siegal (2003). They basically use the same research model leaving out the adoption variable. The information whether the document was already validated (by a committee) or not was added as a peripheral cue. Source credibility is represented by the position and an experience rating of the document author. The experiment is conducted with undergraduate business students. The findings are surprising since higher argument quality led to lower usefulness ratings. The authors explain this with more length of documents with higher argument quality. Source credibility had no effect on perceived usefulness. Only the validation variable positively affected usefulness ratings.

Kayhan and Bhattacherjee (2010) study the use of knowledge repositories (KR) under two different governance regimes, expert and community governance. Accordingly, they add *credibility of governance mechanism* as a peripheral cue to the original ELM. Their dependent variable is the intention to use the knowledge which leads to actual use. The paper does not report empirical results since it is a research in progress.

Li (2013) analyzes the effect of training in an Enterprise Resource Planning (ERP) system on the intention of trainees to use it. She does not model elaboration variables of ELM, cognitive ability and motivation, but adds normative and informational influence as variables. These are influenced by the elements of source credibility and argument quality and influence themselves the formation of attitude that is modeled as a tripartite construct (consisting of affective response, cognitive response, and behavior intention). The results confirm ELM predictions and show, in addition, that cognitive response is much more crucial for the formation of behavior intention than affective response. Jung, Srite, Haseman, and Jung (2013) also studied the attitude toward an ERP system but the emphasis of the research was on students education in ERP systems in a university rather than on their use at work.

In summary, except for Fadel et al. (2008), ELM was mostly but not completely confirmed. Some uncertainty remains about certain moderation effects and peripheral cues: Communication between trainer and trainee (Bhattacherjee & Sanford, 2006) or information exchange via e-mail (Sussman & Siegal, 2003) typically happen among familiar partners. This means, the source of information is personally known to the information recipient. If the informant is known to the information recipient, task-specific criteria may be overshadowed by the personal relationship or "source likeability" (Bhattacherjee & Sanford, 2006). Sympathy or antipathy, competition among individuals, or other aspects that are not related to the task are mixed with task-related criteria. Therefore, it cannot be known whether the influence is based on the personal relationship or on (cues about) the informant's knowledge, experience, or another task-related feature. Task-related credibility of informants should depend on task-specific criteria like problem relevant experience or on the community view, esp. in a collaborative setting.

We advance knowledge on information influence by designing an experiment, as described below, for cases where co-workers do not know each other personally. This is not an unrealistic situation since in big organizations computer-mediated communication and collaboration often take place between partners who do not know each other personally. This is especially the case in organizations with many (international) locations. We design the experiment in such a way that source credibility can be measured without interference from personal relationships and possible prejudices, i.e. source likeability.

Research on information influence can also be based on other conceptual models (Rieh, 2002). We concentrate on ELM-based research because this allows direct comparisons and in order to support the building of cumulative knowledge on informational influence within IS and across disciplines. Table 1 briefly summarizes the reviewed literature.

3. Model development and hypotheses

ELM models attitude as the dependent variable which is influenced by argument quality and peripheral cues. However, recent IS research building on this framework extends or exchanges the dependent variable with variables such as usefulness, intention to use, and (actual) use rather than measuring attitude before and after a stimulus (Bhattacherjee & Sanford, 2006; Fadel et al., 2008; Kayhan & Bhattacherjee, 2010; Sussman & Siegal, 2003). The aim is to combine the explanation of influence processes of ELM with the strong effects of perceived usefulness on the actual behavior proven by models like TAM (Davis et al., 1989). This modification of the original ELM is justifiable and can clarify the results of persuasion studies as

Table 1
ELM-based research in IS within an organizational setting.

Author(s)	Context	Respondents	Dependent variable(s)	Findings
Mak et al. (1997)	ES	36 students	Acceptance of recommendation	ELM predictions fully apply for a high level of participation in knowledge update but only partially for a low level of participation
Dijkstra (1999)	ES	73 students	Agreement	Students with low elaboration likelihood accept wrong advices more often than those with high elaboration likelihood
Sussman and Siegal (2003)	Advice	63 consultants	Perceived information usefulness, information adoption	All ELM predictions fulfilled
Angst and Agarwal (2004)	CRM	116 bank employees	Near-term use, long-term use	ELM confirmed but compliance is more important for long-term usage than internalization; no reduction of actual usage occurs if near-term usage is determined by identification rather than internalization; internalization is not more important than identification as a determinant for long- and short-term usage
Bhattacherjee and Sanford (2006)	DMS	81 city hall employees	Perceived usefulness, attitude, IT usage intention	ELM was confirmed except for the moderating effect of job relevance on the path between source credibility and perceived usefulness
Fadel et al. (2008)	KMS	223 students	Perceived knowledge usefulness	Argument quality has a negative influence on knowledge usefulness. No moderating effects from involvement or expertise found
Kayhan and Bhattacherjee (2010)	KR	n.a.	Intention to use, knowledge use	No empirical validation of the research model
Li (2013)	ERP	123 ERP users	Affective response, cognitive response, behavior intention	Affective response has no significant influence on behavioral intention. Moderating influences of normative and informational social influence were not confirmed

described below. Social psychological research has shown that attitude is a broadly defined construct consisting of three underlying components: affect, cognition, and behavior (Rosenberg & Hovland, 1960). While affect describes an emotional response and behavior means an overt response to a certain stimulus, the cognitive component is characterized by beliefs, knowledge structures, or perceptions as a response to the stimuli. Given this tripartite structure of attitude, it is ambiguous to measure attitude as one construct and, therefore, necessary to specify the component which is the focal point of a research project (Breckler, 1984) if not all components are considered.

Most persuasion studies in social psychology rely on the cognitive component of attitude because the stimuli are logical arguments or information (Cacioppo & Petty, 1979; Greenwald, 1968; Sternthal, Dholakia, & Leavitt, 1978). Since our stimulus, a report in a BI portal, contains information that supports a cognitive task, we apply this well-proven approach and concentrate on perceived usefulness as the cognitive component of attitude as our dependent variable. In the context of IS and ELM, this is also strongly supported by results in Li (2013) as reported above. Since we cannot measure actual long-run report reuse in an experiment, we employ perceived usefulness as its strongest predictor.

As described above, the central route of persuasion is based on the quality of information. In cases when more than a simple piece of information is conveyed, like a whole report in our case, this aspect is usually described as argument quality. A BI report "argues," for example, that a plan is (not) being met, that some organizational units perform better than others, that a relationship between two variables exists, or something similar. As defined above, perceived argument quality relates to information completeness, lack of ambiguity, and correctness. Obviously, an incomplete or unclear report (e.g., missing column headings in a table) would be difficult to comprehend and use. Hence, we hypothesize:

H1. A high argument quality has a positive effect on the perceived usefulness of the report.

In general, ELM suggests that if the information recipient's expertise on the topic is not sufficient, he resorts to peripheral cues in the evaluation process (Petty & Cacioppo, 1986). The above mentioned studies on information adoption have identified perceived source credibility as a major peripheral cue in IS. However, in the two most cited studies, the informant and the information recipient have known each other. Consultants received advice via e-mail from peers in their company (Sussman & Siegal, 2003) and course participants received information from their course instructor (Bhattacherjee & Sanford, 2006). We cannot know in these cases whether credibility was based on sympathy toward the informant or her expertise as perceived by the information recipient. If an organization desires that information is not judged based on source likeability, but supports credibility cues, a different experimental set-up and different cues must be used.

Kelman (1961) attributes source effects to three kinds of social influences: internalization, identification, and compliance. Accepting information from sources with high expertise and integrating this information into one's own cognitive system is called internalization. Identification describes the phenomenon that individuals tend to hold similar opinions as reference persons or groups. Compliance refers to conforming to a powerful source (a person or a group of people) on the basis of rewards and punishments (Karahanna & Straub, 1999). Our experiment is designed in such a way that respondents do not know each other personally and, thus, do not stand in a hierarchical relationship. Compliance cannot be assumed under such conditions since rewards and punishments imply a hierarchical relationship between the parties concerned (Petty & Wegener, 1998). Power in an organization is often legitimated by the hierarchical relationship between people

(Koslowsky & Schwarzwald, 2001). Thus, social influence processes in our research context can be assigned to identification and internalization but not to social compliance. We operationalize them as explained in the following.

First, we turn to possible identification cues. The usefulness of a report to other users can be displayed via usage or subscription statistics. Within BI portals usage or subscription statistics can be easily collected. Usage statistics disclose actual demand for the content. For example, they are given in social networks in the form of "X users have looked up your profile last week" or in article repositories in the form of "This paper has been downloaded x times last month." The figures can be interpreted as indicators of interestingness of content. Subscription usually indicates an evaluation based on the consumption of the content. The number of users subscribing to some content or distributing it can be found in various social networks and micro blogging services (e.g., retweets or following people on Twitter). We choose a subscription figure because it can be interpreted as the extent of endorsement for the respective report (Pee, 2012). Hence, we hypothesize:

H2. A high number of report subscriptions has a positive effect on the perceived usefulness of the report.

More explicit evaluations of a specific content by other users are commonly displayed on e-commerce sites in form of user ratings and recommendations (e.g., amazon.com). These reflect the users' opinions of the quality of products or content. Meredith and O'Donnell (2010) suggest that this function should also be included in BI systems. Research on the effect of ratings in B2C-settings suggests that ratings are especially effective if the rating is supplemented by a rationale (Willemsen, Neijens, Bronner, & de Ridder, 2011). However, an evaluation of report content may be also perceived as an "e-valuation" of the report author. In an organizational setting, authors may be hesitant to contribute reports fearing that negative report ratings may reflect on them unfavorably. But raters, too, may be hesitant and biased in rating their peers' contributions (Toegel & Conger, 2003). Therefore, we do not use user ratings as an identification cue. Obviously, this is a question of organizational culture which different organizations may answer differently.

Internalization is the second relevant social influence process that can be observed in our study. An information recipient (the BI report user in this case) internalizes the opinion of others more likely if the information was created by an expert source (Kelman, 1961). In enterprises, the hierarchical level can be seen as an indicator of experience and expertise which means that a high position of an informant signals a high task-related credibility. Weisband, Schneider, and Connolly (1995) have shown in several experiments that persons with high status exhibit more influence than persons with a lower status. The disclosure of the hierarchical level of the report author has been recommended for BI systems (Böhringer et al., 2009). It can be signaled, for example, through the display of the position title. Hence, we hypothesize:

H3. A high hierarchical level of the report author has a positive effect on the perceived usefulness of the report.

An alternative cue that supports internalization could be the expert level of the report author. In privately used social media the expert status of a contributor may be indicated, for example, by the number of stars, a label (e.g., "novice" or "expert"), or a "karma" figure. The status is gained either just based on activity within the application and/or based on other users' evaluations of the author's contributions (e.g.: "Rate how valuable this review was to you"). We did not incorporate such cues because the number of contributed reports may be strongly correlated with the job function (which is already partly contained in the position title) and peer evaluations could again lead to unintended effects.

A central assumption of ELM is that users take the central or the peripheral route depending on their ability and motivation to elaborate information (Petty & Cacioppo, 1986). Accordingly, these are the two characteristics of information recipients we want to analyze in this context. In IS research, individual motivation has been operationalized by job relevance (Bhattacherjee & Sanford, 2006). It is assumed that the motivation of employees to elaborate information produced by an application rises if this very application is an important part of their daily job and may influence their work performance. In contrast, users in jobs where this application is perceived to be less relevant may spare the effort of elaborating the argument and rely on peripheral cues. In other words, job relevance moderates information influences.

The ability dimension of ELM is captured in IS research as recipient expertise, user expertise, or prior knowledge (Bhattacherjee & Sanford, 2006; Pee, 2012; Sussman & Siegal, 2003). We choose the term user expertise. Expert users can assess the provided information well on the basis of their domain and, in our case, based on methodological and software knowledge. For example, understanding the display of multidimensional data in a two-dimensional table requires some experience or expertise. Experienced users do not need to rely on peripheral cues as novices (Bhattacherjee & Sanford, 2006). Novice users do not have enough expertise to assess the information in detail. They are forced to search for other indicators and rely on peripheral cues and heuristics (Petty & Cacioppo, 1986). Hence, we hypothesize:

H4. A high elaboration likelihood, formed by job relevance and user expertise, has a positive moderating effect on the relationship between argument quality and perceived usefulness.

H5a. A high elaboration likelihood has a negative moderating effect on the relationship between report subscriptions and perceived usefulness.

H5b. A high elaboration likelihood has a negative moderating effect on the relationship between hierarchical level of report author and perceived usefulness.

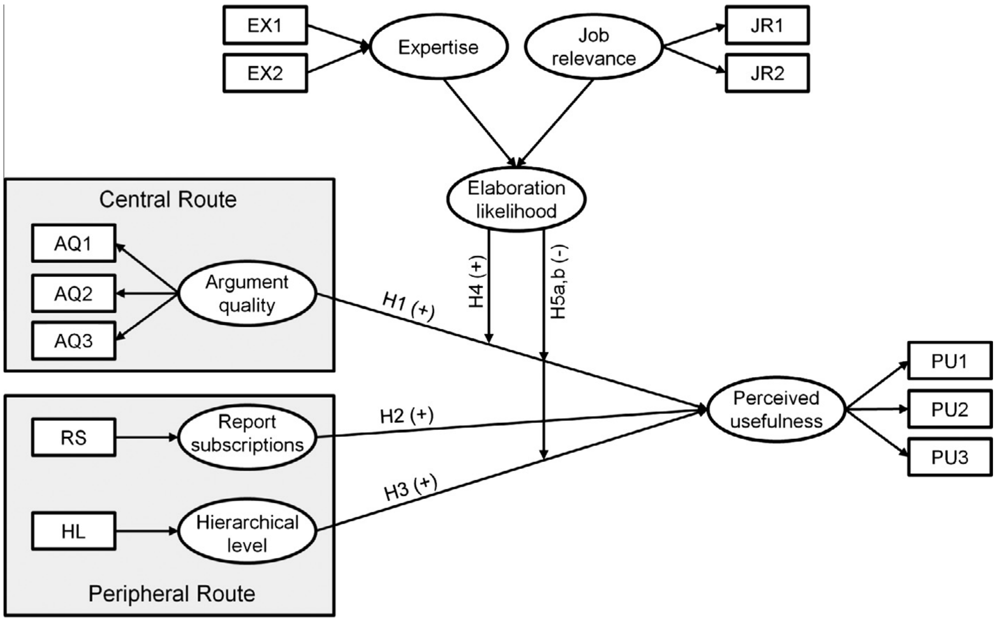


Fig. 2. Research model.

Fig. 2 summarizes our research model.

Our model mostly resembles the model of Fadel et al. (2008) but the unexpected results reported in that study (negative effect of argument quality, no moderation effects) call for a reexamination. There is also an important difference in peripheral cues. The *validation* cue used in Fadel et al. (2008) in addition to cues about the document author represents a formal approval by a small group. Therefore, there is no construct that relates to identification with the community. We measure this aspect by the construct *report subscriptions* which indicates the report usage by the user community. Finally, surveying undergraduate students is a good research start, but if findings should be transferable to companies, it is mandatory to conduct research with working professionals as is done here.

4. Method

4.1. Experimental design

We asked selected participants to evaluate a screen shot of a BI portal mock-up containing a report supplemented by social cues. The cognitive task was to compare the sales performance of individual branches among each other and with the average sales of the company based on the presented report. It is a slightly changed example from a source on good practices of information presentation in reports, widely respected in companies in German speaking countries (Hichert, 2007). We chose it because it presents a good and a poor quality report based on the same data. Both reports are given in Appendix B. The "good quality" report explicitly compares each branch with the average performance and displays exact sales figures for each year. The "poor quality" report displays the exact sales figures only for the most current year while all others are only shown as bar charts. Average branch performance is not displayed but needs to be induced from eight individual bar charts. The displayed information has been reduced compared to the original source in order to ensure that it is visible on all devices; the displayed dates have been adapted so that the report appears to have been generated in 2013. The survey was conducted in German and has been translated for presentation in this article.

As indicated above, we want to create a situation where no personal relationship exists between informant and information recipient. This set-up is automatically given in our experiment since the report author is a fictive person. However, even if people do not know each other, a photo of the report author may induce feelings like sympathy, trust, or prejudices based on gender, age, race, or other aspects. Since we want to avoid such effects, we only show a silhouette of the report author instead of a picture. This is not unusual but a custom in social media when people do not want to show their photo to everybody. Since the name often indicates the gender and may indicate ethnicity or a certain national origin, we provide only the initial of the first name and a last name that is common in Germany.

The peripheral cue relating to internalization, hierarchical level, does not disclose any personal characteristics of the report author. These considerations also apply to the identification cue. Böhringer et al. (2009), for example, provide in their prototype a photo and further information about report users. We do not incorporate this suggestion in our experiment since it creates similar issues like providing a photo of the report author. In addition, in Germany, for example, tracking of employees in corporate social media or in other applications is usually not allowed if it is not demanded by the work context. Displaying names of users who ran a report would not be allowed without the (unlikely) consent of the working council. All social data we use are or can be easily utilized in real systems without conflict with even strong data privacy regulations.

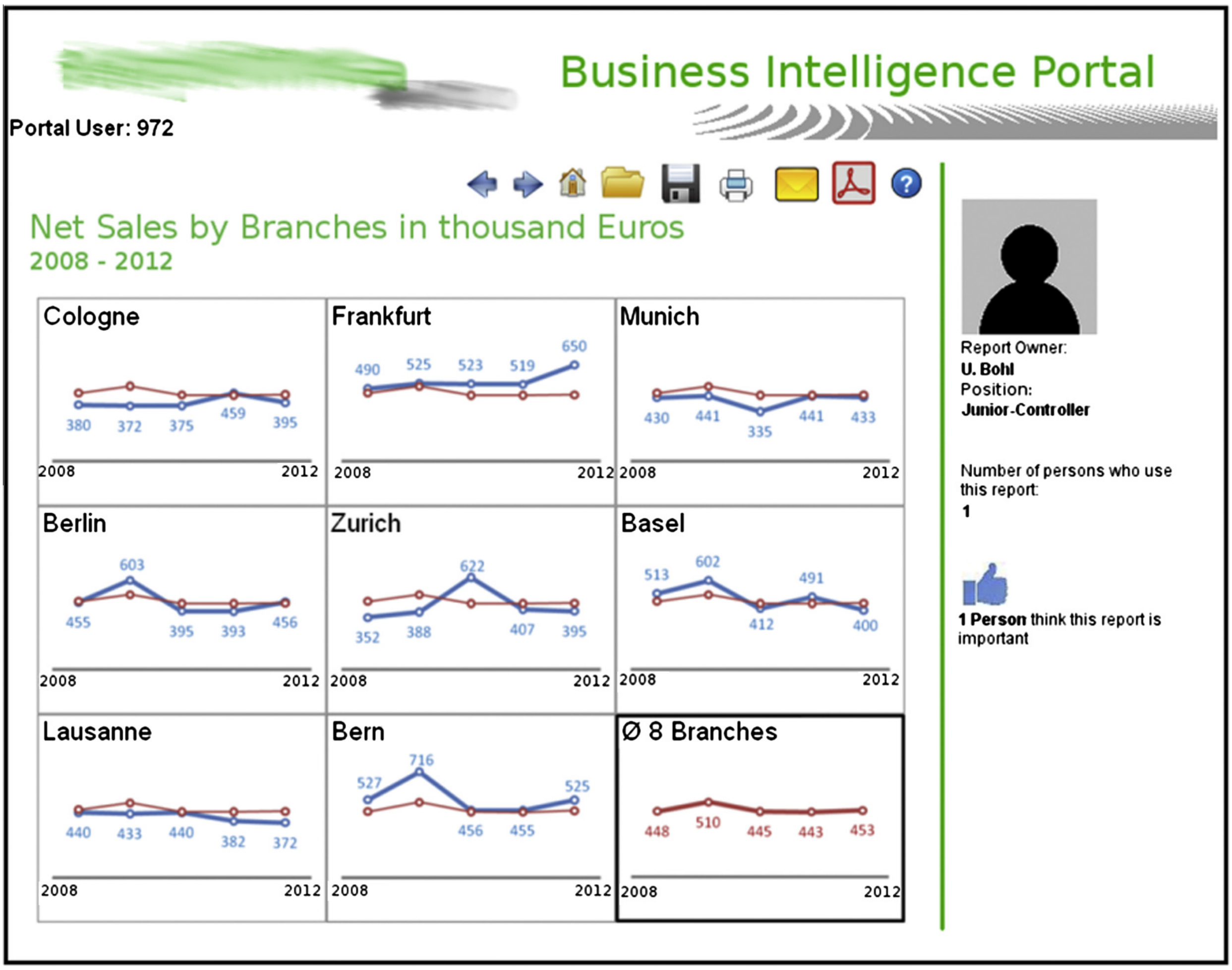


Fig. 3. A research scenario.

Due to the limited number of participants, only a limited number of scenarios can be employed. Therefore, we set for each of the variables just two values, a high and a low value (see also Lim, 2013), so that the participants could easily interpret these cues, if they wanted to include them in their assessment. The cue "number of people who use this report" was set to a low number (1) or a high number (30) and the hierarchical level was set to either a junior or a senior position. The two report versions and the two social cues are all displayed randomly with a high or a low value. This design results in a $2 \times 2 \times 2$-matrix with 8 treatment combinations. Each respondent was randomly assigned to one configuration for assessment. Fig. 3 shows one scenario.

4.2. Experiment participants and data collection procedure

The survey was conducted in Spring 2013. The target group consisted of knowledge workers from different functional areas (finance, marketing, logistics, IT) and different hierarchical levels (staff, line, and managers). They live in German-speaking areas, including the countries Germany, Austria, Switzerland, and Belgium. 1750 addressees were randomly chosen from a contact list of customers and prospects of a medium-size BI consultancy and contacted by e-mail. They were characterized in the data base as BI report designers (26%), BI users (66%), or having no BI experience (9%). The e-mail contained a link to the online-survey which also contained the mock-up. Participation was on a voluntary basis without any reward. All participants were advised that this was a scientific survey and promised a summary of the results. 334 persons opened the link and 178 completed the survey (53.3%). Some responses had to be eliminated because answers to measurement items were incomplete. Records in which the processing time was so short that it cannot be assumed that the survey was processed with care (less than 60 s) and records that were apparently filled out following a certain pattern (e.g. always the same value) were also eliminated. The only rational explanation for such behavior is that the participants were interested in the survey results.

The data cleansing process resulted in 141 useable records. When we compare the BI proficiency of these respondents with all addressed contacts, then there is no statistically significant difference between the distribution of the respondents and the above given distribution of contacts. Given the eight scenarios, there are about 17.6 observations on average for each research scenario; this can be considered sufficient for statistical purposes (cf. Constant, Kiesler, & Sproull, 1994; Mak et al., 1997). The average age of respondents is slightly less than 40 years. The majority of participants held a senior position (as a manager or specialist) and was male. The job position and the age of the participants show a high variation indicating a sufficient amount of variance in elaboration likelihood based on these variables. An overview of the participants' characteristics is shown in Table 2.

4.3. Measurement

The research model contains three manipulated constructs which were captured by dichotomous variables. Argument quality, hierarchical level, and report subscriptions were coded 0 for the poor quality report/low hierarchical level/low number of report subscriptions and 1 for good quality report/high hierarchical level/high number of report subscriptions. Dummy coding was applied since the number of participants for each scenario is unequal (cf. Streukens, Wetzels, Daryanto, & de Ruyter, 2010).

We also measured perceived argument quality and used this variable in the calculations rather than the quality level set by (Hichert, 2007) (as low or high) because the perceived quality of identical reports may be different by different people (Lee, Strong, Kahn, & Wang, 2002). Furthermore, perceived source credibility was measured to check the manipulation of both peripheral cues. Perceived usefulness and elaboration likelihood (expressed by expertise and job relevance) need to be operationalized with appropriate items and measurement scales. Reliable and established scales were taken from previous studies while the item wording was tailored to the specific research context. The items of argument quality and perceived usefulness were adopted from Sussman and Siegal (2003). Items measuring perceived source credibility were drawn from (Kubiszewski, Noordewier, & Costanza, 2011) and elaboration likelihood was captured using items from Bhattacherjee and Sanford (2006). All statements could be rated on seven-point agreement scales with the extremes being 1 (strongly disagree) and 7 (strongly agree). All constructs are measured with reflective items except for user expertise which is formed by the items *knowledge of Business Intelligence* and *knowledge of collaborative systems*. Thus, user expertise relates to methodological or tools knowledge rather than domain knowledge. The latter was not necessary for the chosen cognitive task as explained in Section 4.1. With respondents from different functional areas and different industries, a task requiring extensive domain knowledge could not have been selected. Job relevance referred to BI in general since no fictive report could have been really relevant for the participants. However, the experimental setting was clear to the participants and there can be no doubt that they were able to relate the example to their own company setting. Supporting figures are presented below.An overview of all items is included in Appendix A.

5. Results

5.1. Measurement model

Partial least squares (PLS) were used to test the presented research model because PLS has several advantages over (co)variance-based approaches to test factorial designs: PLS is less demanding regarding the sample size and distribution (Chin, Marcolin, & Newsted, 2003; Reinartz, Haenlein, & Henseler, 2009), measurement models can be controlled for errors, and both reflective and formative indicators can be calculated simultaneously (Streukens et al., 2010). Path coefficients, moderating effects, and quality criteria were computed with SmartPLS 3 (Ringle, Wende, & Becker, 2014). The quality of the reflective measurement models can be assessed by the criteria indicator reliability, composite reliability, convergent validity, and discriminant validity (Henseler & Fassott, 2010). The results are shown in Table 4. The recommended minimum value of indicator reliability is 0.7. In our study, all indicators load well above this threshold (0.87 and higher) and can therefore be described as highly significant. Composite reliability is calculated via the internal consistency reliability (ICR) and should surpass the value of 0.7 (Nunnally & Bernstein, 1994). All constructs fulfill this criterion and reach ICR scores of 0.93 and above. Convergent validity can be assessed using the average variance extracted (AVE) (Fornell & Larcker, 1981).

Table 2
Demographics.

Characteristic	Count	Ratio (%)	Characteristic	Count	Ratio (%)
Gender			Position		
Male	83	59	Junior specialist	12	9
Female	56	40	Specialist	34	24
Not specified	2	1	Senior specialist	47	33
Age			Manager	41	29
<30	25	18	Others	1	1
30–39	42	30	Not specified	6	4
40–49	52	37			
>49	21	15			
Not specified	1	1			

Table 3
Quality criteria of the measurement model.

Reflective constructs	ICR	AVE	Indicator reliability		
Argument quality	0.93	0.81	AQ1 = 0.92	AQ2 = 0.87	AQ3 = 0.91
Source credibility	0.96	0.89	SC1 = 0.94	SC2 = 0.95	SC3 = 0.94
Job relevance	0.98	0.97	JR1 = 0.98	JR2 = 0.99	
Perceived usefulness	0.98	0.93	PU1 = 0.96	PU2 = 0.98	PU3 = 0.97
Formative constructs	**VIF**	**Bivariate correlation**	**Indicator weights**		
User expertise	4.22	0.87***	EX1 = 1.17**	EX2 = −0.20 n.s.	
Elaboration likelihood	2.01	0.71***	EXL = 1.07***	JRL = −0.10 n.s.	

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

Table 4
Descriptive statistics.

Scenario	n	Argument quality		Perceived usefulness		Job relevance		Expertise	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
LQ/LH/LS	21	3.30	1.77	2.57	1.50	5.41	2.07	4.98	2.03
LQ/LH/HS	20	3.83	1.54	3.23	1.73	6.05	1.16	5.38	1.51
LQ/HH/LS	19	3.88	1.58	3.95	1.76	5.34	2.03	4.79	1.88
LQ/HH/HS	15	3.33	1.57	4.57	2.14	4.27	2.28	3.40	2.05
HQ/LH/LS	15	4.40	0.88	4.43	1.39	5.47	1.22	5.03	1.61
HQ/LH/HS	22	4.32	1.63	4.98	1.78	5.18	1.59	4.59	1.74
HQ/HH/LS	14	4.50	1.25	4.68	1.03	4.90	1.76	4.18	1.64
HQ/HH/HS	15	4.64	1.57	4.90	2.10	5.87	1.37	5.40	1.72
Total	141	4.00	1.56	4.10	1.86	5.34	1.76	4.75	1.84

Notes: SD = standard deviation, HQ = high quality report, LQ = low quality report, HH = high hierarchical level, LH = low hierarchical level, HS = high number of subscriptions, LS = low number of subscriptions.

If 50% of the construct's variance is explained AVE reaches 0.5 which is regarded as a sufficient level of convergent validity (Götz, Liehr-Gobbers, & Krafft, 2010). All examined constructs show very good AVE scores above 0.81. Discriminant validity is determined by the Fornell–Larcker criterion which measures if the AVE of a specific latent variable is higher than any squared correlation of this construct with another examined variable (Fornell & Larcker, 1981). All constructs in the research model fulfill this criterion.

Elaboration likelihood was calculated using a second-order construct (cf. Jarvis, Mackenzie, Podsakoff, Mick, & Bearden, 2003) formed by user expertise and job relevance. For this, latent variable scores were computed for each of the two components of elaboration likelihood in smartPLS. Afterward, the latent variable scores (EXL and JRL) were used as formative indicators for elaboration likelihood. This approach complies with the recommendations to compute hierarchical constructs given in Wetzels, Odekerken-Schröder, and van Oppen (2009).

The formative constructs user expertise and elaboration likelihood can be assessed by looking at multicollinearity and the significance of indicator weights (Chin, 1998; Diamantopoulos & Winklhofer, 2001; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). The variance inflation factor (VIF) measures multicollinearity and should not surpass the value of 10 (Reinartz et al., 2009). The values of 4.22 and 2.01 are well under the recommended upper limit and indicate low multicollinearity. One of two indicators for user expertise and elaboration likelihood is significant at a 95% and the other at 99% level. However, EX2 and JRL show very small negative indicator weights and low significances. Cenfetelli and Bassellier (2009) argue that indicators with a small contribution can be interpreted as absolutely but not relatively important and should remain in the measurement model under the conditions that the bivariate correlation is high and that they cover distinct facets of a construct. Since both indicators fulfill these criteria, they were kept in the model.

Age and position are personal characteristics that could impact elaboration likelihood. However, they correlate each significantly with expertise and cannot be added but they could be used instead of expertise to reflect ability. This leads to less robust results and is, therefore, not reported here. Gender could be considered by conducting separate calculations for each gender in order to compare path coefficients. However, this leads to too few observations for most scenarios. We are also not aware of any literature suggesting gender effect in this context.

5.2. Preliminary analyses

The descriptive statistics of each scenario are given in Table 3 showing that the participants perceived a lower argument quality in all scenarios with the low quality report than in all scenarios with the high quality report. The computation of the bivariate correlation between the latent variable scores of perceived argument quality and the dichotomous manipulation variable argument quality confirms this observation. A value of 0.27 (significant at $p < 0.01$) indicates that participants could well differentiate between the good and poor quality report.

The computation of the correlation between the latent variable scores of both peripheral cues (modeled as one formative construct) and perceived source credibility yields a correlation coefficient of 0.14 (significant at $p < 0.05$). This states that the manipulation of the peripheral cues was perceived by the participants in the manner intended.

There is a significant correlation ($p < 0.05$) between job relevance and questionnaire completion time. This supports ELM assumptions and the experimental design: participants with higher job relevance elaborated longer on the questions. This would not have happened if they did not see any relationship between the fictive report and their job demands.

5.3. Structural model

A two-step approach was applied to test the structural model. The research model was firstly evaluated without moderating effects and secondly moderating effects were included before calculating the results.

The path coefficients of influence of argument quality, report subscriptions, and hierarchical level of report author on perceived usefulness are positive and significant supporting the Hypotheses H1, H. and H3. These results persist when interaction terms are included. The explained variance of perceived usefulness by our research model is 0.37 with direct effects only. Including direct and indirect effects results in an increased R^2 value of 0.47 which lies between moderate and substantial explained variance according to Chin and Newsted (1999).

In Hypotheses H4, H5a, and H5b, we theorize that elaboration likelihood has a positive moderating effect on the path from argument quality to perceived usefulness and a negative effect on the relationships between the peripheral cues and perceived usefulness. The moderating effects of elaboration likelihood are confirmed empirically. All path coefficients of moderating effects are significant. However, the interaction effect between report subscriptions and elaboration likelihood is positive contrary to Hypothesis H5a. The detailed results for all hypotheses are summarized in Table 5.

6. Discussion

6.1. Interpretation

The influence of argument quality as the central route and the influence of report subscriptions and hierarchical level of report author as peripheral cues conform to ELM. Argument quality has clearly the highest impact on perceived usefulness. Identification and internalization processes, modeled by peripheral cues, also took place. This also answers our first research question about factors that influence perceived usefulness of a report.

These influences are moderated by BI systems expertise and job relevance of BI as job-related characteristics in the following way (research question two): Both characteristics form elaboration likelihood which increases the impact of argument quality on perceived usefulness. The theory-based expectations are also met for the moderation of the impact of the hierarchical level. However, the effects of elaboration likelihood on the influence of report subscriptions do not confirm our expectations based on ELM. Report subscriptions represent the community view of the report. Respondents with high elaboration likelihood pay attention to this view despite the low quality of the report. Our analysis of the respondents shows that those with high expertise, a formative part of elaboration likelihood, are often report designers. They seem to give credit to the low quality report based on report subscriptions, perhaps following the proverb "Bait the hook to suit the fish, not the fisherman."

Table 5
Results of the structural model.

Hypothesis	Path (DV = perceived usefulness)	Path coefficient (direct effects)	*t*-value	Path coefficient (direct + indirect effects)	*t*-value	Hypothesis confirmed
H1	Argument quality	0.55***	7.04	0.48***	6.46	Yes
H2	Report subscriptions	0.15**	2.17	0.10*	1.60	Yes
H3	Hierarchical level of report author	0.19***	2.78	0.18***	2.74	Yes
H4	Argument quality × elaboration likelihood			0.23**	2.26	Yes
H5a	Report subscriptions × elaboration likelihood			0.16**	2.12	No
H5b	Hierarchical level of report author × elaboration likelihood			−0.08*	1.55	Yes

Notes: DV = dependent variable.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

While ELM assumes that decision makers exclusively take either one route or the other, Petty and Cacioppo (1986) admit the possibility that arguments and peripheral cues may also occur simultaneously. The suspicion of additive impacts of both routes is backed by research using the heuristic–systematic model of information processing (Maheswaran & Chaiken, 1991). Decision makers seek information to reduce their uncertainty (Shannon & Weaver, 1949) and may not want to ignore any piece of information. Therefore, we hypothesize that participants with high elaboration likelihood also observe peripheral cues when argument quality is low rather than immediately rejecting the message, here a BI report. Similar to job relevance, there is a small but significant correlation (at $p < 0.05$) between expertise and questionnaire completion time. This means that participants with higher expertise used more time to answer the questions although they should be able to assess the usefulness of the report quicker than participants with lower expertise. This is a further indication that users with high expertise possibly use peripheral cues in addition to argument quality.

Our results confirm the above cited assumption of Petty and Cacioppo (1986) that the central route and peripheral route may co-occur. In the IS context, this means, that if the analysis of argument quality leads to doubts, information recipients may still resort to peripheral cues. In other words, while information recipients with low expertise can only take the peripheral route, information recipients with high expertise may still take this route, possibly if they remained in doubt after taking the central route. For them, the central and the peripheral route are not alternatives but may complement each other.

6.2. Limitations and future research

The study has several limitations. To obtain acceptable results with a limited number of participants, the study was limited to two social cues. Future research should investigate the impact of additional (or other) cues and a combination of task-related and task-unrelated cues. However, affective attitudes toward report authors (or other report users) that may be based on prejudices will be difficult to determine in an organizational setting since respondents will be more inclined to answer politically correct fearing that their identity could be easier disclosed than in a public survey.

Our result that the two routes of persuasion can complement each other for information recipients with high elaboration likelihood leads to the question about the sequence of information examination. It could be that they first examine the arguments because they have the ability and motivation to do so and then, if not persuaded yet, use peripheral cues. However, it could also be that they first notice peripheral cues that are usually easy to assess and then examine the arguments. The experiment would need to be designed in such a way that respondents also reveal the sequence of information use.

It is further of interest to discover what weights are assigned to the two routes if they complement each other. In a setting of two directly communicating parties and based on a moral hazard model that includes payoffs for the informant and information recipient, Dewatripont and Tirole (2005) show that extreme values of peripheral cues may "crowd out" the communication of task-relevant information while intermediate values enhance it. In an experiment like ours, this would mean, for example, that the variable report subscriptions should be set to several values ranging from very low to intermediate to very high values. This would, however, lead to more scenarios and require more respondents.

The study also needs to be extended to other cultural environments since cultural aspects play a major role in the behavior of people (Hofstede, Hofstede, & Minkov, 1991). For example, people in Germany have a low power distance and may, therefore, be less influenced by the hierarchical level of an informant than people in countries with high power distance.

7. Managerial implications and conclusion

The results of our study have direct implications for the enhancement of BI systems by selected social media features. Our research has shown that disclosure of the hierarchical level of the author and the number of report subscriptions are peripheral cues that receive attention from users. The community view could be strengthened by adding votes for reports. However, the use of voting schemes should be carefully considered since it may create unintended effects (e.g., asking close colleagues to vote favorably for one's report even if they do not use it) and adaptive behavior (e.g., not contributing reports because of fear of poor voting scores) that diminish the positive value of crowd wisdom expressed through voting. Other cues may also grab user attention but care should be taken not to overload users with peripheral cues and distract their attention from report content. Therefore, managers should consciously choose how many and which cues to offer. Report reuse reduces time and cost for report design but it is most important that users with low expertise use the right report. Therefore, great care has to be taken that the previous phase of report retrieval delivers a good fit between user needs and available reports. This can be supported, for example, through tagging, another feature made popular through social media. In this case, each report designer could be asked to generate a set of descriptors for the reports she develops.

Organizations should also consciously decide whether they want to add information that may invoke source likeability (or the opposite). While organizations usually prohibit anonymous contributions in internal applications, there are also contexts where less disclosure about personal characteristics of contributors helps to concentrate on task-related issues.

In practice, supporting evaluation of report usefulness leads to another benefit. As shown in Hertzum and Pejtersen (2000), employees search for documents not only because of their content but also to find document authors who may be experts on the subject of the document. Then, they interact with them directly. In our case, a user who discovers relevant reports may be assured of report authors' expertise if he receives information on the number of subscriptions for the different reports as one cue.

We have developed a model to analyze influence processes in the context of BI. The model is based on ELM and it can explain a considerable percentage of variance in perceived usefulness. Users of BI reports are mostly influenced by argument quality but peripheral cues, here the number of report subscriptions and the hierarchical level of the report author, also influence their perception of report usefulness. We ensured with our research design that these results are not biased by source likeability.

The number of report subscription reflects a community view that has been often researched in public social networks. We have identified that it also receives considerable attention in an organizational setting, even when information recipients do not need to rely on it to evaluate the information.

We have empirically confirmed the suspicion that the central and peripheral routes can complement each other. More research is needed to clarify how they exactly complement each other, in terms of sequence of their evaluation and how their influences are aggregated to derive at an overall assessment of the information received.

Appendix A. Construct definitions and respective items

A.1. Perceived usefulness

This is the degree to which people believe that the use of a specific IS artifact would improve their working performance (Davis et al., 1989). The items are adapted from Sussman and Siegal (2003) where they were taken from Bailey and Pearson (1983) and range from "strongly disagree" to "strongly agree" on a seven-point agreement scale.

PU1. The processing of data by this report is valuable to solve the task.
PU2. The processing of data by this report is informative to solve the task.
PU3. The processing of data by this report is helpful to solve the task.

A.2. Perceived argument quality

This is the extent to which a user of an application perceives the provided information to be complete, unambiguous, meaningful, and correct (Wand & Wang, 1996). The items are adapted from Sussman and Siegal (2003) where they were taken from Bailey and Pearson (1983) and range from "strongly disagree" to "strongly agree" on a seven-point agreement scale.

AQ1. The processing of data by this report is complete.
AQ2. The processing of data by this report is consistent.
AQ3. The processing of data by this report is accurate.

A.3. Perceived source credibility

This is the degree to which people believe that the information provider is a reliable information source. The items are adapted from Kubiszewski et al. (2011) and are measured on a seven-point agreement scale ranging from "strongly disagree" to "strongly agree."

SC1. The report is trustworthy.
SC2. The report is believable.
SC3. The report is reliable.

A.4. Elaboration likelihood

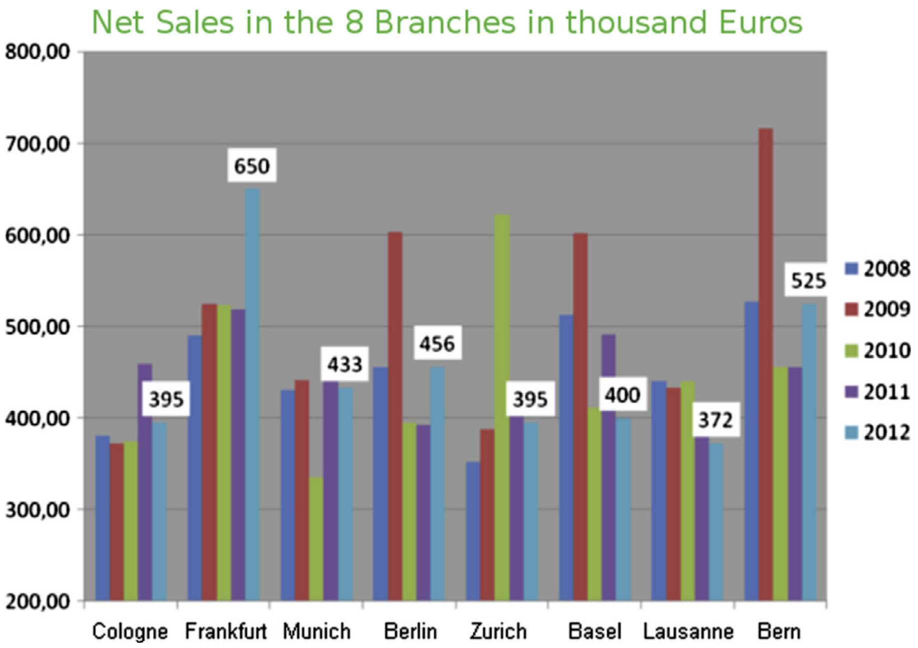
This relates to the motivation and the ability to evaluate given information and elaborate the main arguments (Bhattacherjee & Sanford, 2006). Ability is represented by expertise (Bhattacherjee & Sanford, 2006) which is measured on a seven-point agreement scale ranging from "strongly disagree" to "strongly agree."

EX1. I am a knowledgeable user of Business Intelligence systems.
EX2. I am a knowledgeable user of collaborative software.

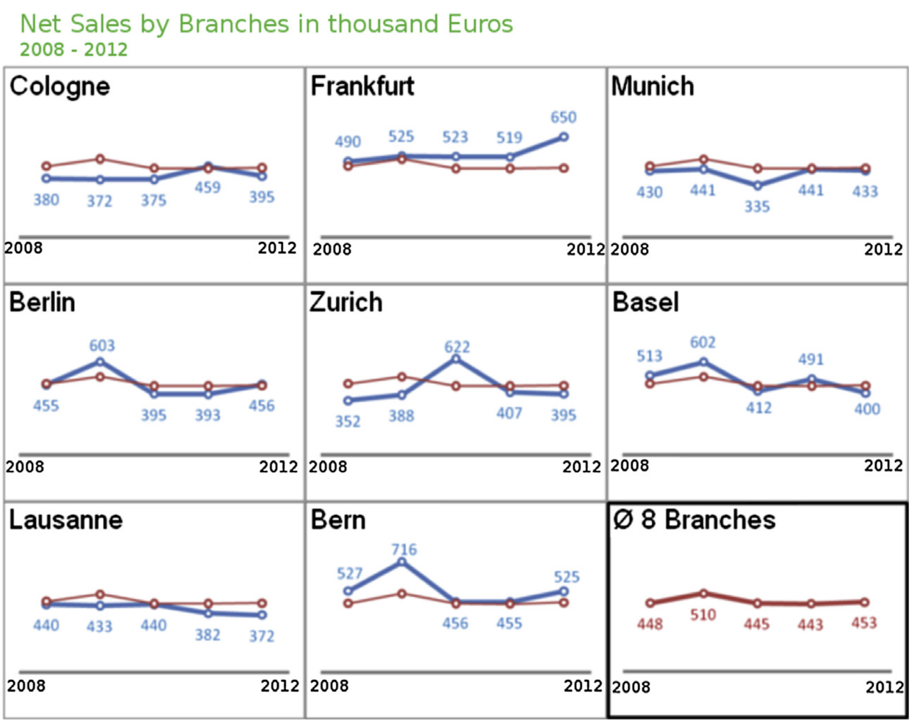
Motivation is represented by job relevance (Bhattacherjee & Sanford, 2006) which is measured on a seven-point agreement scale ranging from "strongly disagree" to "strongly agree."

JR1. Using Business Intelligence systems is important for my job.
JR2. Using Business Intelligence systems is appropriate for my job.

Appendix B



Poor quality report



Good quality report

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Essay IV

Titel

Initial and Continued Knowledge Contribution on Enterprise Social Media Platforms

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Konferenz

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INITIAL AND CONTINUED KNOWLEDGE CONTRIBUTION ON ENTERPRISE SOCIAL MEDIA PLATFORMS

Research in Progress

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Abstract

In recent years, social media has entered enterprises as a tool for internal communication, collaboration, and knowledge management. However, it has been reported that knowledge contribution rates are low which raises questions on the reasons for it and how to improve the situation. To address these questions, we take a deep look into the individual knowledge contribution process using an integrative model that explains the initial formation of the intention to contribute knowledge and the continued knowledge contribution. Towards this goal, we apply the theory of reasoned action, the social exchange theory, and the belief-adjustment model. In this research in progress, we present our research model and a test covering the first part of the model, the formation of the intention to contribute knowledge. The results suggest that social exchange theory and theory of reasoned action are well suited to explain this phenomenon and that they build a good basis for the second part of the longitudinal study.

Keywords: Knowledge sharing, Enterprise social media, Social exchange theory, Belief-adjustment model.

1 Introduction

About one decade ago, social media started to make the leap from the private realm to use within companies where they become enterprise social media (ESM). ESM include tools such as blogs, social networks, or wikis that allow employees to communicate with other organization members, to identify particular co-workers, and to jointly create and edit content (Leonardi et al., 2013). This way, ESM offer new, open, and inexpensive alternatives to traditional knowledge management (KM) systems (von Krogh, 2012). Actionable knowledge mainly results from collaboration. ESM provide an appropriate infrastructure to capture the created knowledge and share it with co-workers (Avram, 2006). Although the tools are suitable for various aspects of KM, knowledge contribution on ESM platforms is still very low (e.g., Ebner et al., 2008). This observation and the forecast that 80% of all social business efforts will miss their objectives until 2015 (Gartner, 2013) raise the question about the underlying reasons.

To answer this question in sufficient depth, we focus on the first phase of KM as defined by Alavi and Leidner (2001): knowledge creation. Efficient knowledge creation and the further three main processes storage/retrieval, transfer, and knowledge application are the key objects of KM and should be supported by corresponding systems. Extant research on knowledge sharing will serve as a starting point to identify the determinants of knowledge contribution on ESM platforms while research on IS continuance can help to identify factors fostering or preventing continued contribution (as reviewed in section 2).

Even though traditional KM systems and ESM are mostly used for the same purpose in KM, it is often overlooked that KM has to consider new ways of knowledge collaboration when changing from traditional KM systems (centralized, controlled) to ESM (less-structured, mostly voluntary, emergent uses) (cf. von Krogh, 2012). While technology acceptance research (e.g., utilizing the technology acceptance model) addresses the changes caused by new technical characteristics, we emphasize the deviating individual motivations behind knowledge creation and sharing in the new environment. Therefore, a context specific and integrative analysis is necessary to get a comprehensive insight into the knowledge contribution process of employees on an ESM platform. The objective of this study is (1) to identify (de)motivating cost and benefit factors influencing the initial decision to share knowledge via an ESM platform and (2) to examine how training and actual usage affect continued knowledge sharing.

The paper is organized in six sections. The next section gives a brief review of relevant literature on KM using ESM, knowledge sharing, and IS continuance to determine possible research gaps. Then, we develop the research hypotheses and present the research model. In the next following two sections, we describe the research method and present results from our first survey representing the first phase of the research model. Finally, we discuss the results and conclude with a brief summary on limitations and contributions of this research.

2 Previous research

A growing body of research examines the use of ESM in KM by focusing on specific tools such as blogs or wikis (e.g., Raeth and Smolnik, 2010; Wagner, 2004) or processes such as knowledge adoption (e.g., Alpar et al., 2015; Engler, 2014). Additionally, various factors influencing knowledge sharing in ESM have been studied in recent literature: gender (Chai et al., 2011), trust (Chai and Kim, 2010), organizational climate (Kügler et al., 2015), and social capital (Chiu et al., 2006). However, an empirically tested theoretical foundation of cost and benefit factors of knowledge contribution in ESM and knowledge contribution over time has not been presented yet. Two streams of research can build the basis to address this gap: research on knowledge sharing/contribution and research on information systems continuance.

Predictors of knowledge contribution have been extensively researched. The most influential papers chose different approaches to explain this phenomenon. Bock et al. (2005) employ the theory of reasoned action (TRA) developed by Fishbein and Ajzen (1975) as a theoretical framework and focus on extrinsic motivators, social-psychological factors, and organizational climate. Kankanhalli et al. (2005) look at the topic through the theoretical lens of social exchange theory (SET). They theorize that perceived intrinsic/extrinsic benefits and costs trigger the use of electronic knowledge repositories. This influence is moderated by contextual factors. Wasko and Faraj (2005) emphasize the social capital perspective of knowledge contribution and model inter alia structural, cognitive, and relational capital to determine the amount of contributed knowledge.

Information systems (IS) continuance research is dominated by the expectation confirmation theory (Bhattacherjee, 2001). The theory posits that IS continuance is a function of the expected performance before and the experience after actual use. A longitudinal approach is presented by Kim and Malhotra (2005) in which they use constructs from technology acceptance research. The results of their empirical test conformed with their assumptions about the change of these variables over time based on the belief-adjustment model developed by Hogarth and Einhorn (1992). He and Wei (2009) combine these two research streams to examine continued knowledge seeking and contribution and emphasize the difference between the predictors of seeking and contributing knowledge.

3 Research model and hypotheses development

To explain the initial formation of the intention to contribute knowledge and the potential changes over time caused by actual contribution and training, we combine TRA (Fishbein and Ajzen, 1975), SET (Thibaut and Kelley, 1959), and the belief-adjustment model (Hogarth and Einhorn, 1992). The resulting research model is presented in figure 1.

TRA builds the central element of the research model. Fishbein and Ajzen's (1975) theory suggests that a behavioral intention is formed by an individual's attitude and subjective norms. Attitude is defined as beliefs about the perceived consequences of performing a behavior and the expected outcomes of these consequences. Subjective norms represent the influences of the social environment on the thoughts and behavioral intentions of an individual. Behavioral intention then results in actual behavior.

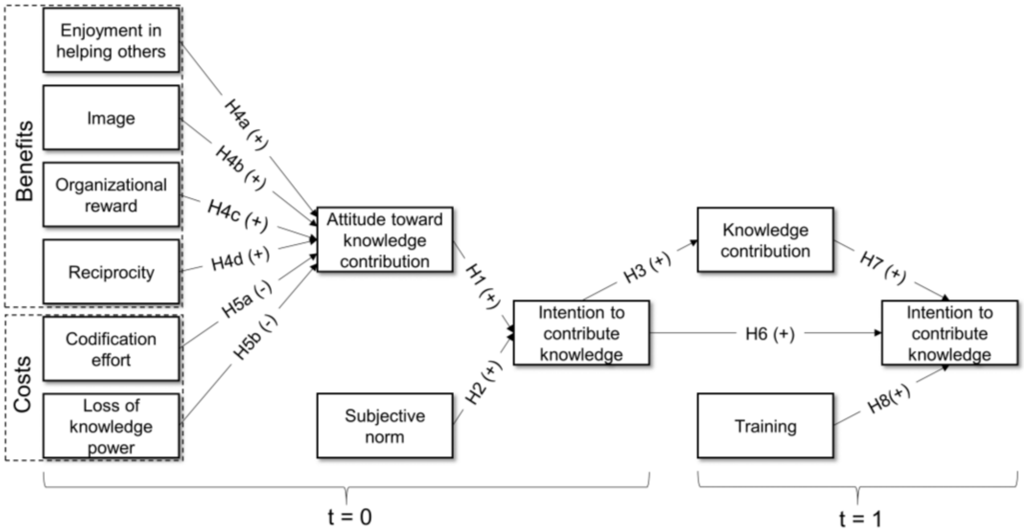

Figure 1. Research model.

The application of TRA in this research context provides the explanation why individuals are more likely to have a positive intention to contribute their knowledge to the ESM community if they have a favorable attitude toward knowledge contribution: they think that the consequences and outcomes can help to fulfill the initially planned objectives (e.g., improvement of their image in the community or reciprocal knowledge contribution). This works in the opposite direction, too. An employee is less likely to have a strong intention to contribute knowledge if s/he has an inherently negative attitude toward knowledge contribution. Since employees, especially in an ESM community, do not work isolated from each other, social interaction plays an important role in the context of knowledge sharing (Avram, 2006). The influence of the social environment can work through the mechanisms of compliance, identification, internalization, or any combination of these (Kelman, 1961). Thus, an employee who either complies with the company's rules, identifies with the company's values, or internalizes norms in favor of knowledge-sharing is more likely to develop a positive intention to contribute knowledge. In summary, we hypothesize:

Hypothesis H1: The more favorable the *attitude toward knowledge contribution* (ATT) is, the greater is the *intention to contribute knowledge* (INT) in t = 0.

Hypothesis H2: The greater the individual's subjective norm (SUB) to contribute knowledge is, the greater is the *intention to contribute knowledge* in t = 0.

In case the intention to contribute knowledge is strong, the actual knowledge contribution will also be strong. Since we measure the intention at pre-implementation time (t = 0), the actual knowledge contribution can only be measured at t = 1.

Hypothesis H3: The greater the *intention to contribute knowledge* in t = 0 is, the greater is the actual *knowledge contribution in* t = 1.

Previous research has established an economic view of knowledge sharing by considering knowledge sharing as a function of benefits and costs (Cohen and Prusak, 2001; Nahapiet and Ghoshal, 1998). This follows the logic of the SET developed by Thibaut and Kelley (1959). Kankanhalli et al. (2005) seize this idea and model the benefit factors *enjoyment in helping others*, *image*, *organizational reward*, and *reciprocity* and the cost factors *codification effort* and *loss of knowledge power* which influence the usage of electronic knowledge repositories. The definitions of the aforementioned constructs can be found in table 1.

	Construct	Definition
Benefits	Enjoyment in helping others (ENJ)	Intrinsic enjoyment felt to help others (similar to altruism).
	Image (IMA)	Reputation gained from the public demonstration of the ownership of knowledge.
	Organizational reward (ORG)	Expected rewards from the organization such as bonus payments, new job opportunities, job security.
	Reciprocity (REC)	Anticipated future help from community members because of knowledge contributions in the past.
Costs	Codification effort (COD)	Time/effort spent to codify knowledge to fit into the system.
	Loss of knowledge power (LOS)	Fear of knowledge contributors to retain less proprietary knowledge to justify a certain organizational power position.

Table 1. Construct definitions, adapted from Kankanhalli et al. (2005).

We adopt this perspective since the social exchange is especially important for knowledge sharing on ESM (as described above). However, we argue that these factors do not directly influence intention or actual behavior. They rather influence intention indirectly as predictors of *attitude toward knowledge contribution* since they represent the belief about the perceived consequences of contributing knowledge which is in turn the core concept of attitude in TRA. Therefore, we hypothesize:

Hypothesis H4: The greater the expected benefits of knowledge contribution (*enjoyment in helping others (a)*, *image (b)*, *organizational reward (c)*, and *reciprocity (d)*) are, the more positive is the *attitude toward knowledge contribution*.

Hypothesis H5: The lower the expected costs of knowledge contribution (*codification effort (a)* and *loss of knowledge power (b)*) are, the more positive is the *attitude toward knowledge contribution*.

The belief-adjustment model (Hogarth and Einhorn, 1992) provides the theoretical background to explain potential changes over time with regard to the *intention to contribute knowledge*. The main statement of the model is that people do not react directly to new stimuli but rather (partially) adjust their prior knowledge on the specific topic to the stimuli. In this scenario, prior knowledge serves as an anchor and new stimuli as adjustments. The model was firstly applied to the IS context by Kim and Malhotra (2005) who explain continued information systems use. They theorize (and provide empirical evidence) that user evaluations follow the same process.

Here, the *initial intention to contribute knowledge* (t = 0) serves as the anchor, and the *intention to contribute knowledge* in t = 1 represents the adjustment.

Hypothesis H6: The stronger the *intention to contribute knowledge* is in t = 0, the stronger is the *intention to contribute knowledge* in t = 1.

Actual *knowledge contribution* is the first stimulus adjusting the *intention to contribute knowledge* over time. Employees who contribute knowledge to the platform learn incrementally how to do it more efficiently and gain experience. This in turn will ease the process of codifying knowledge and lead to a higher perceived usefulness of the system and as a result to a stronger intention to continue contributing knowledge (c.f. Bajaj and Nidumolu, 1998). Therefore, we hypothesize:

Hypothesis H7: The greater the actual k*nowledge contribution* is, the greater is the *intention to contribute knowledge* in t = 1.

The uses of ESM platforms should be emergent (McAfee, 2006). However, previous research suggests that employees may not recognize the full potential of newly implemented ESM immediately (Raman, 2006) or they may be overwhelmed by the functionality which results in a reluctance toward the technology (Turban et al., 2011). Therefore, a passive roll-out strategy of ESM without any top-down support may lead to failure (McAfee, 2009). Facilitating conditions, such as the provision of training, can help to overcome these issues (Venkatesh et al., 2003) and increase the *intention to contribute*. The company where the research took place had a similar experience with the roll-out of the platform in other areas of the company. Thus, training acts as the second stimulus in our research model.

Hypothesis H8: Training has a positive effect on the *intention to contribute knowledge* in t = 1.

4 Research method and data analysis

4.1 Measurement and data collection

To operationalize the theoretical constructs we adopted scales that were proven to be reliable and valid in extant literature. This and the feedback loop with experts from the company enabled us to ensure content validity. The scales for *codification effort*, *enjoyment in helping others*, *image*, *loss of knowledge power*, *organizational reward*, and *reciprocity* are drawn from Kankanhalli et al. (2005). We replaced "electronic knowledge repository" with the actual name of the ESM communty to improve content validity. The items for *attitude toward knowledge contribution* stem from Bock et al. (2005). *Subjective norm* is measured using a second order construct (formative/reflective first order and formative second order). The first order constructs of *subjective norm* are *compliance* (Bock et al., 2005), *identification* (Kankanhalli et al., 2005), and *internalization* (Malhotra and Galletta, 1999). Finally, *intention to contribute knowledge* was drawn from Venkatesh et al. (2012). The items for *knowledge contribution* for the second survey (t = 1) will be adopted from Kankanhalli et al. (2005) while *intention to contribute knowledge* will be captured using the same measures as in t = 0. *Training* will be measured using a yes/no question that will be coded as a dummy variable. In all other cases, items are answered on a Likert-scale ranging from 1 = "strongly disagree" to 7 = "strongly agree".

Using the instrument in t = 0, we conducted a field study with globally dispersed product managers with an engineering understanding from a big multinational engineering company. The engineering background is needed because business customers usually order customized products. The customization process is guided by the respondents who adjust the base product to customer requirements and discuss the new solution with engineers at the headquarters. This should ensure the feasibility of the solution and enables them to exactly calculate the price of the customized product. To foster collaboration and knowledge sharing between the product managers, the headquarters decided to create a community on an ESM platform which provides the functionality of blogs, a forum, a wiki and a social network (based on IBM Connections). The platform was already used in other areas of the company but none of the product managers was using it before. The expectation was that problem solutions developed in one location would be entered into the system so that they can be discussed and eventually reused in other locations. Data for the first survey (t = 0) was collected in November 2013 via self-administered questionnaires handed out to employees shortly before they were granted access to the platform. The second survey (t = 1) is scheduled for the first quarter 2015, about one year after initial use.

All members of the unit (220) received the questionnaires and 105 of them responded (response rate = 48%). Out of the 105 responses, 7 had to be eliminated due to suspicious answer patterns (two alternating values or only a single value) resulting in 98 usable data sets. 21% of the respondents were female and 79% were male and the majority was between 31 and 40 years old which approximately mirrors the gender and age characteristics of the group.

4.2 Data analysis

Partial least squares (PLS) (cf. Chin, 1998) was used to analyze the data because it allows to simultaneously compute formative and reflective measurement models, it is less demanding regarding sample size and the distribution of data, and it is generally recommended for sample sizes smaller than 250 (Reinartz et al., 2009; Streukens et al., 2010). We used the software SmartPLS 3.0 (Ringle et al., 2014) to calculate the model. We first evaluate the measurement models and then assess the relationships between the constructs of the research model.

4.2.1 Measurement model

The criteria indicator reliability, composite reliability, convergent and discriminant validity were assessed to evaluate the quality of the reflective measurement models (Hair et al., 2013). The formatively measured constructs *organizational reward* and *subjective norm* are checked for item multicollinearity and indicator weights.

Indicator reliability can be assessed by looking at the indicator loadings. The loadings should surpass a threshold of 0.7 to indicate sufficient reliability. All items fulfill this criterion as indicated in table 2. Composite reliability was evaluated using internal consistency reliability (ICR) since it uses weighted item loadings and is considered a better reliability measure than Cronbach's alpha (Chin and Gopal, 1995; Fornell and Larcker, 1981). All reflective variables show ICR values above the recommended lower limit of 0.7 (Nunnally and Bernstein, 1994). Convergent validity was checked by assessing the average variance extracted by a measure. A value above 0.5 is considered acceptable (Fornell and Larcker, 1981) and fulfilled for all constructs as shown in table 2.

	Indicator loadings / *weights*				**Average variance extracted**	**Composite reliability / *VIF***
	Item 1	**Item 2**	**Item 3**	**Item 4**		
ATT	0.850	0.848	0.910	0.889	0.765	0.929
COD	0.852	0.808	0.928		0.746	0.898
ENJ	0.913	0.888	0.938		0.834	0.938
IMA	0.720	0.776	0.883		0.650	0.881
INT	0.889	0.894	0.925		0.816	0.930
LOS	0.951	0.971	0.968		0.928	0.975
ORG	*-0.261*	*0.703*	*0.616*		/	*1.252*
REC	0.861	0.915	0.839		0.761	0.905
SUB	*0.225*	*0.101*	*0.944*		/	*1.380*

Table 2. Measurement model assessment.

Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell and Larcker, 1981) which states that the square root of the AVE (shown in the shaded fields in table 3) should be greater than the correlation of the construct with any other construct in the research model. The results in table 3 confirm discriminant validity in our data.

	ATT	**COD**	**ENJ**	**IMA**	**INT**	**LOS**	**ORG**	**REC**	**SUB**
ATT	0.875								
COD	-0.223	0.864							
ENJ	0.480	-0.259	0.913						
IMA	0.304	0.022	0.392	0.806					
INT	0.652	-0.264	0.471	0.246	0.903				
LOS	-0.373	0.236	-0.252	-0.048	-0.267	0.963			
ORG	0.093	0.101	0.182	0.338	0.056	0.197			
REC	0.353	0.116	0.493	0.452	0.385	-0.068	0.318	0.872	
SUB	0.525	-0.238	0.483	0.316	0.758	-0.178	0.060	0.409	

Table 3. Correlations between constructs and Fornell-Larcker criterion.

Finally, the indicators of the formative constructs show a low multicollinearity which is indicated by variance inflation factor (VIF) values of 1.252 and 1.380 lying well below the recommend upper limit of 10 (Reinartz et al., 2009). All but one indicator weight show effects in the postulated direction. Item

1 for *organizational reward* shows a negative sign. Since the bivariate correlation with the construct is high and the items cover different facets of one construct item 1 was kept in the model (c.f. Cenfetelli and Bassellier, 2009).

We checked for common method bias (CMB) using Harman's single-factor test because all variables were measured using data from one survey. A substantial amount of common method variance would be indicated, if a single factor would explain the majority of the variance of all measured constructs (Podsakoff et al., 2003). A single factor explains 22.95% of the variance in this study which indicates that CMB is not a considerable issue.

4.2.2 Structural model

With the measurement models being valid and reliable, the hypotheses of the research model in t = 0 were tested (H1, H2, $H4_{a\text{-}d}$, and $H5_{a,b}$). The results of the evaluation are summarized in figure 2. We divided the level of hypothesis confirmation into three groups: those which are unambiguously significant (meet the common standard in IS research of $p < 0.05$), those which have high effect sizes (expressed by path coefficients) and would have been significant with a slightly larger sample size ($p < 0.10$, marked with a t in figure 2), and those which are clearly insignificant.

Starting from this premise, the examined relationships of TRA are significant (H1 and H2 confirmed) showing a stronger effect for *subjective norm* than for *attitude*. The explained variance of *intention to contribute knowledge* can be classified as substantial ($R^2 = 0.67$) according to Chin (1998). The evaluation of the costs and benefits as predictors for attitude show mixed results. Both cost factors *codification effort* and *loss of knowledge power* lower the *intention to contribute* with the latter having the stronger influence. *Enjoyment in helping others* has the strongest positive effect. *Reciprocity* also increases the *intention to contribute* knowledge as posited. However, no significant effects are obtained for *organizational reward* and *image*.

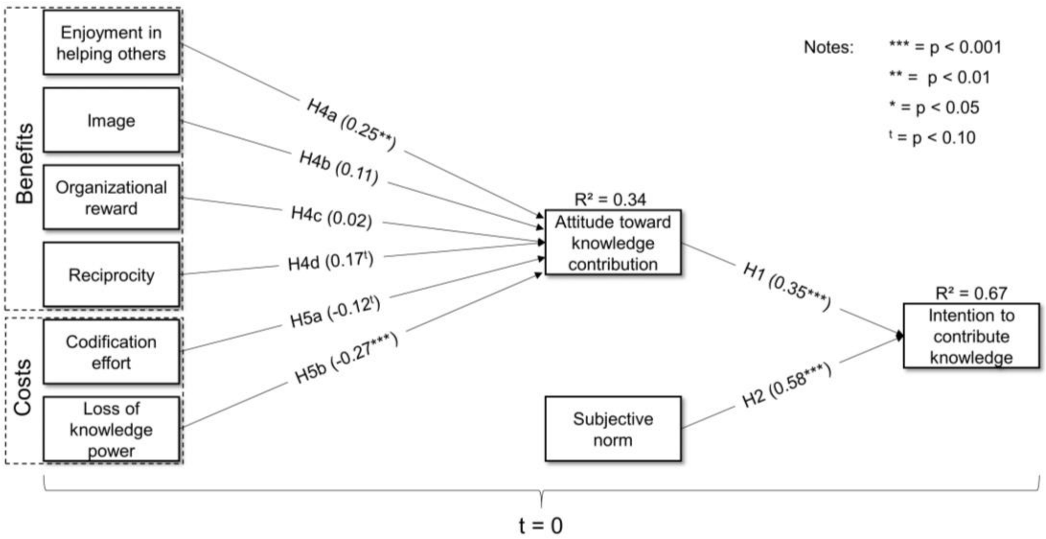

Figure 2. Results of the PLS analysis in t = 0.

5 Discussion

Since only the data collection for t = 0 is completed until now, we proceed with the discussion of hypotheses H1, H2, $H4_{a\text{-}d}$, and $H5_{a,b}$. The predictors of the central part of the research model, that follows TRA, show strong effects on *intention to contribute*. Similarly to comparable studies (e.g., Bock et al. (2005)) we obtain a higher effect of *subjective norm* than *attitude*. However, deviating from Bock et al.'s result, the difference between the path coefficients is considerable. We attribute the substantially higher effect of subjective norm to the application environment. In contrast to traditional knowledge repositories, the contributions in internal ESM platforms are highly visibly linked to the contributor (identified, e.g., by photo or name) and, therefore, contributors may be more susceptible to their social environment.

The hypotheses concerning the cost factors *codification effort*, *loss of knowledge power*, and the benefit factors *enjoyment in helping others,* and *reciprocity* were confirmed, suggesting that the variables influence *attitude to contribute knowledge* in the theorized manner.

Contrary to the theorized assumptions and previous findings (e.g., Ba et al., 2001; Wang et al., 2009), we found that an *organizational reward* would not foster the *attitude to contribute knowledge*. This result can be very well explained by looking deeper at the nature of extrinsic rewards. On the one hand, rewards may motivate in the short term but, on the other hand, they may harm personal relationships because for each person who wins, there is a number of people who perceive a loss. When employees compete for a limited number of incentives, they will very likely begin to see each other as competitors rather than collaborators (Kohn, 1999) contradicting the original idea of ESM platforms for knowledge exchange. Furthermore, rewards on the basis of measured indicators (e.g., number of posts) can lead to the perception of a close monitoring (e.g., by supervisors) which in turn might undermine the motivation to share knowledge.

Similarly, the possibility to build up a reputation by showing the ownership of knowledge (*image*) was not found to be a significant predictor of *attitude* as opposed to findings from (Hall, 2001; Kankanhalli et al., 2005; Wasko and Faraj, 2000). Two reasons may cause this counterintuitive but interesting result. First, when published knowledge is trivial or flawed and eventually publicly revised, image may suffer so that respondents weigh the potential loss more than a potential gain in image (Raeth et al., 2012). Second, strong teamwork and collaboration norms may reduce the need for an improved image in such a way that it is no longer a motivating factor for knowledge contribution (Kankanhalli et al., 2005).

6 Conclusion, limitations, and implications

The presented study aims to uncover both the factors determining the initial intention to contribute knowledge and the causes for continued contributions. For this, we develop an integrative model explaining the predictors of knowledge contribution and continued contribution and present empirical results on the attitudes to contribute knowledge in the pre-implementation phase of an ESM. We show that SET and TRA build a solid foundation for step two of our study. However, our study has two limitations. First, all respondents are employees of one company which limits the generalizability. However, the product managers stem from different countries and work in different locations all over the world. Second, the completion of the questionnaire was voluntary and, hence, a self-selection bias can occur. Since we found that age and gender distributions in the survey are very similar to their distributions in the whole population of product managers in that firm, we assume that self-selection is not a major issue in this study.

The completed research project (including step two in $t = 1$) seeks to advance theoretical knowledge by helping to get a comprehensive understanding of knowledge contribution on ESM platforms. Besides identifying individual costs and benefits of knowledge sharing on ESM, the study will be among the first to longitudinally observe ESM use and the success of ESM training.

In practice, our results can have important implications for the management of knowledge centered ESM communities. At this point in time, the most important implication for practice is that only intrinsic factors play an important role when considering sharing knowledge within the company. Extrinsic motivators in the form of reward systems do not promise to foster knowledge contribution. Due to the large influence of intrinsic factors and the individual subjective norm, managers should try to embody the intention to contribute knowledge and promote the intrinsic benefits rather than extrinsic rewards. Furthermore, we expect the results of step two to answer the question which factors influence continued knowledge contribution on ESM platforms.

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Essay V

Titel

Understanding Online Product Ratings: A Customer Satisfaction Model

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Understanding online product ratings: A customer satisfaction model

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ABSTRACT

Online product ratings have become a major information source for customers, retailers, and manufacturers. Both practitioners and researchers predominantly interpret them as a reflection of product quality. We argue that they in fact represent the customer's satisfaction with the product. Accordingly, we present a customer satisfaction model of online product ratings which incorporates the customer's pre-purchase expectations and actual product performance as determinants of ratings. We validate our model by applying it to two datasets collected at the German website of Amazon.com. The results indicate that both factors have a significant influence on online product ratings, supporting the proposed interpretation of ratings.

1. Introduction

Along with the growing diffusion of e-commerce, online product reviews have become a major information source for customers, retailers, and manufacturers. On the one hand, reviews and ratings contributed by online shop customers provide product information for prospective consumers, thereby reducing their uncertainty about the product (Chen and Xie, 2008). Consistently, research has shown that they affect sales in various contexts (e.g., Chevalier and Mayzlin, 2006; Lin et al., 2011; Park et al., 2007). On the other hand, online retailers and manufacturers increasingly rely on customer feedback to enrich their marketing strategy (Chen and Xie, 2008; Cui et al. 2012), to adjust product listings (e.g. via relevance sorting), and to create additional revenue streams (Mudambi and Schuff, 2010). For these reasons, it is not surprising that nearly all major online retailers such as Amazon.com or Ebay.com have implemented product rating functionalities.

Researchers, mainly from the fields of marketing and information systems, have adopted the topic and not only started to study the effects of online product ratings (e.g., on sales) but also their nature and determining factors. A common assumption of prior studies in the latter stream is that the baseline of a product's online ratings reflects its true quality. Various biases such as social dynamics or cultural influences were introduced to account for the unexplained part of the variance. However, empirical evidence suggests that online ratings do not accurately reflect a product's true quality (e.g., Hu et al., 2006; Koh et al., 2010). Since the influence of ratings on sales remains unaffected, retailers are left in an uncomfortable situation: it is difficult for them to adjust marketing strategies on the basis of online product ratings without knowing what they actually reflect.

Hence, the objective of this study is to find out what really builds the baseline of online product ratings and thereby refine their current interpretation. We argue that the weak explanatory power of product quality for online reviews is not only caused by actual biases: it is mainly caused by product ratings reflecting customer satisfaction than being a valid measure for product quality. This approach does not solely rely on product quality as the baseline for the rating but also integrates the customer's expectation of the product in the pre-purchase phase. Correspondingly, we present a customer satisfaction model of online product ratings based on the considerations of Fornell (1992) and Westbrook and Reilly (1983). We model the customer's pre-purchase expectation of the product and the actual performance as predictors of online ratings using structured equations. We validate our model by applying it to two datasets (digital cameras and televisions) collected from the German website of Amazon.com. The results indicate that both a customer's expectation of a product and the actual performance significantly influence the ratings customers assign to a product, supporting the proposed interpretation of online product ratings.

Several other observations in the datasets can help to get a more comprehensive view of online product ratings and are worth mentioning. First, we find that online ratings carry some percentage of unobservable information that cannot be predicted (using metrics from the website). Second, the data shows indications for confirmation, acquisition, and under-reporting biases.

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Fig. 1. Word cloud of Amazon review (the bigger the word, the more frequent it was used in the reviews).

In the next section, we review the extant literature on product ratings. In Section 4.1.1, we elaborate on the theoretical background of customer satisfaction and present our research model. In Section 4.2.1, we discuss the measurement of the latent constructs and describe the collection of data. There, we also present the results of our analysis, which are discussed in Section 5. In Section 5, we conclude this paper by explaining its implications for practice and research, its limitations, and possible directions for future research.

2. Review of literature on product ratings

Online product ratings have been researched from various perspectives, which can be classified according to whether they investigate their antecedents or outcomes. The first category rather includes studies examining the influence of online product ratings on consumers' purchasing decisions. In most of these studies, a significant positive influence is found (e.g., Lin et al., 2011; Mauri and Minazzi, 2013; Park et al., 2007; Sun, 2011), although it may diminish over time (Hu et al., 2008). For a more detailed review we refer to Moe and Trusov, (2011) as this paper belongs to the second category that investigates the factors on which ratings depend.

Research on the antecedents of product ratings mainly focuses on different biases influencing the rating score. Wulff and Hardt, (2014) and Koh et al., (2010) find evidence of cultural differences among raters. The latter authors also find that product ratings do not reflect true (perceived) product quality, a result also obtained by Hu et al., (2006). Sridhar and Srinivasan, (2012) find that prior customer ratings weaken the effect of product experience but can either increase or turn around the effect of product failure, depending on how the latter is addressed. Moe and Schweidel, (2012) link a customer's rating to his decision to rate. They find that the influence of prior customers' ratings on a customer depends on how often this customer rates products.

However, most of these studies suffer from two major shortcomings. First, the products which are analyzed are often books or movies. The individual ratings of these products can be assumed to depend strongly on personal taste and not on a common ground. Second, the true quality of a product is measured via surveys among non-experts. Therefore, they may not be well-suited to assess a quality effect in online product ratings, limiting the validity.

3. Hypothesis development

Previous research on online ratings has started from the premise that the baseline of online ratings represents the true quality of a product (cf. Hu et al., 2006; Moe and Trusov, 2011), including statements such as “each posted online review is an assessment of a single individual's perceived quality of a product” (Koh et al., 2010, p. 374). The conclusion of these studies is that online ratings do not accurately reflect product quality. They attribute this fact to various biases instead of questioning their underlying premise. Since sales heavily depend on online ratings, misinterpreting their baseline can be the root of misguided actions of retailers and manufacturers.

We argue that online product ratings are rather an expression of customer satisfaction than a pure quality assessment. The construct customer satisfaction is a central concept in marketing research measuring individual-level satisfaction with products and services (Yi, 1991). It is defined as a function of the customer's expectation and product performance (Fornell, 1992; Fornell et al., 1996). Expectation is conceptualized as the perceived probabilities of what the consequences of a purchase will be (Oliver, 1980). Performance refers to the perceived quality of the product after the purchase. Instead of being tied to a purely post-purchase quality-centered perspective (as online product ratings are assumed to be in prior research), the definition of customer satisfaction adds the perspective of pre-purchase expectations. In the following, we outline why online product ratings reflect customer satisfaction with the product and thereby include the consideration of both: the customers' expectation of the respective product and the performance they perceive after buying it.

A strong indication that online product ratings reflect customer satisfaction was found by searching through the full-text reviews on Amazon.com. For this, we used Amazon review data consisting of reviews from 1996 until 2014 (McAuley et al., 2015). The complete dataset contains 7,834,166 reviews of products in the category electronics. We created a word cloud (Fig. 1) using a randomly selected subset (10% of the complete dataset) to better understand the meaning behind online reviews. Stop words were removed and same words in plural/singular or different tenses were consolidated to condense the findings into a cloud depicting the top 100 words.

Besides words describing the general experience with the product (“great” was found in 36.6% of the reviews), product parts and product categories (e.g., cable (11.2%), camera (18.8%)), the cloud includes evidence for the proposed interpretation of online ratings (e.g., expect (5.3%), price (17.8%), and reviews (5.0%)). Additionally, we searched the full dataset for “expect” (as a word or part of the words expected and expectation) and found that 571,939 reviews (7.3%) include this word. When compared to the search result for the word “quality” (1,167,525 reviews, 14.9%), these figures strongly indicate that expectation is not a marginal phenomenon in review texts. Since the score of individual online ratings is consistent with the corresponding text (Ganu et al., 2009), it is very likely that they are based on more than a pure assessment of product quality. Instead, the baseline effect of online ratings includes both, pre-purchase expectations and the post-

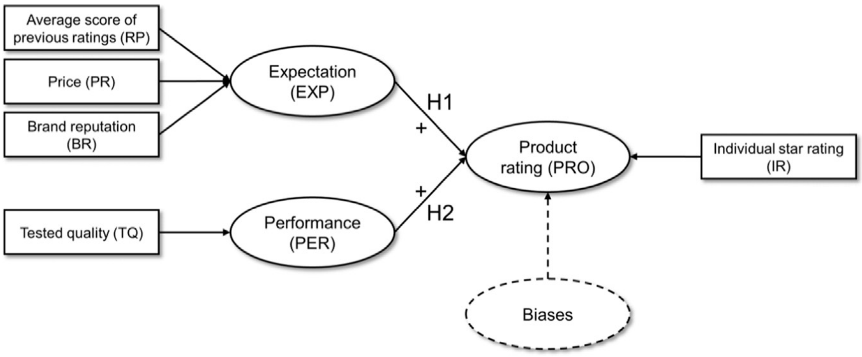

Fig. 2. Consumer satisfaction model of online product ratings.

purchase performance. Hence, we assume that customer satisfaction reflects the baseline of the rating score.

Biases may distort this baseline. Online ratings can, therefore, be expressed as a function of the baseline effect and biases. Because the latter stream has already been extensively researched as described in the previous section, we now elaborate in more detail on pre-purchase expectations, post-purchase performance, and the mechanisms behind their effect on the online product rating score. The resulting research model (including the measurement models discussed in the following section) is presented in Fig. 2.

An explanation for the underlying effect of pre-purchase expectations on online product rating scores is provided by the belief-adjustment model (Hogarth and Einhorn, 1992; Bolton, 1998). It describes the order of belief updating over time as a process of anchoring and adjustments. The central message of the belief-adjustment model is that individuals do not directly react to a new stimulus but rather adjust their prior expectations on the specific topic to the new stimulus while sustaining in the vicinity of the original anchor (cf. Oliver, 1980). Thus, pre-purchase expectations should have a positive impact on satisfaction. It was found to be applicable in various contexts. This leads us to assume that this process also takes place in the context of online shopping and the pre-purchase evaluation of products. First, customers form an expectation what the product might be like on the basis of information found on the product website. In a second step, they adjust this anchor within a reference frame set by the initial judgement when being confronted with the product's performance after the purchase and delivery. Hence, we hypothesize:

Hypothesis H1. : Pre-purchase expectations (EXP) have a positive impact on the score of online product ratings (PRO).

The direct effect of performance on satisfaction is supported by the value-percept disparity model developed by Westbrook and Reilly, (1983). They posit that satisfaction is a general perception based on the evaluation of customers' experiences with a product. A high satisfaction can, therefore, only be achieved if a product is able to fulfill the customer's needs. This mechanism is consistent with findings from Churchill and Suprenant (1982). The results of their study suggest that satisfaction with a durable good can be predicted by the product performance to a considerable extent. Further studies also support this direct effect of performance on satisfaction (Anderson and Sullivan, 1993; Fornell, 1992). Transferred to the online environment, this means that online product ratings are indeed influenced by the experienced quality of the product, as assumed by prior research (e.g., Koh et al., 2010). The product's performance should, therefore, have a positive effect on the score of online ratings. Thus,

Hypothesis H2. : A product's post-purchase performance (PER) has a positive impact on the score of online product ratings (PRO).

4. Research method and data analysis

4.1. Measurement and data collection

The research model was tested using crawled data of cameras and televisions to address the two major shortcomings of prior research as described above. Books and movies can be classified as experience goods while cameras and televisions are search goods (cf. Nelson, 1970, 1974). The ratings of experience goods heavily depend on personal feelings, cannot be evaluated on the basis of specific characteristics, and may vary across different individuals (Mudambi and Schuff, 2010; Weathers et al., 2007). Whereas the beauty of a book or a movie is in the eye of the beholder, it is pointless to argue about objective measures such as battery lifetime or viewing angel stability. Search goods such as cameras and televisions can be evaluated using a more systematic approach (Cui et al., 2012) including rather objective criteria such as technical functions (e.g., megapixels) into the evaluation process, hence, increasing rating reliability.

4.1.1. Expectation

The aim of this research is to identify factors that constitute the score of online ratings made by customers of an online shop. For this, we adopted the customer's perspective and focus on quantitative data that can be included in the evaluation by quickly overlooking the product's description on the website (see Fig. 3). Accordingly, expectation was captured using three indicators that can be evaluated by customers this way before buying the product: the average score of previous ratings, the product price, and brand reputation. While the score of previous ratings is the major source of information for online customers (Koh et al., 2010; Cui

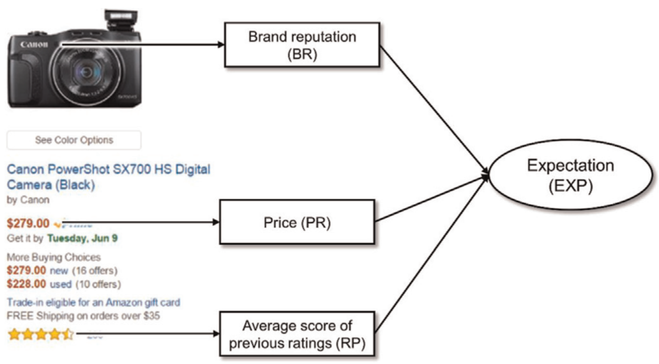

Fig. 3. Product description on amazon.com and measurement model of expectation.

et al., 2012), product price and brand reputation have been identified as the most important extrinsic (not product-inherent) quality indicators in the offline world (Zeithaml, 1988). The measures of the construct expectation are formative since a change in the indicators cause a change in the construct rather than reflecting it. Furthermore, there is no reason to expect that the indicators are necessarily highly correlated (Jarvis et al., 2003).

In online shops, usually two directly observable quantitative indicators of the customer feedback are accessible: the number and the score of previous ratings. While a high number of previous ratings may enhance the subjective weight of the score of previous ratings, the latter affect the customer's expectation directly. The influence of customer ratings on the customer's perception can be explained by different manifestations of social power. Five bases of social power have been identified: expert power, legitimate power, referent power, reward power, and coercive power (French and Raven, 1959). The customer's decision to rely on customer ratings can be attributed to the two mechanisms referent and expert power (Engler, 2014). Referent power describes the effect that individuals seek to hold similar opinions with their social environment to achieve personal satisfaction by conformity. The second phenomenon can occur even if conformity is not the root of social power. French and Raven, (1959) state that conformity with the group's opinion (here: the group of raters) can also be caused by expert power. For this, the customer regards the aggregated wisdom of previous ratings as an expression of expertise. We measure the score of the previous ratings by averaging all star ratings of the respective product up to the time of the individual rating.

Price is the second indicator forming expectation. It has been identified to influence the perceived quality of the product in offline and online shops (e.g., Dodds et al., 1991; Rao and Monroe, 1989; Chen and Dubinsky, 2003). Customers consider the product price as an indicator for product quality because they believe that the interplay of supply and demand leads to an order of competing products on a price scale in accordance with their quality (Scitovszky, 1944). The price information was collected in the same time period as the performance indicator.

A vast body of research (e.g., Dodds et al., 1991; Jacoby et al., 1971; Zeithaml, 1988) has found that not only price but also brand reputation also influences the expected performance of a product. Similarly to the effect of price on the expected performance, the brand name can add information to the product that can otherwise not be accessed in the pre-purchase phase (Zeithaml, 1988). Customers assume that companies do not want to threaten a positive reputation by selling poor quality products (e.g., Nguyen and Leblanc, 2001; Yoon et al., 1993). Therefore, we model brand reputation as the third indicator constituting expectation. A well-proven measure for brand reputation is RepTrak® (Ponzi et al., 2011). RepTrak® is measured by the Reputation Institute and is based on an emotion-based measure of corporate reputation (Reputation Institute, 2014). We used the Global RepTrak® 100 score which is based on data collected in 15 countries (including Germany) to calculate the model. National differences are not as important as customer differences for high-tech goods such as consumer electronics and customers of these products are globally similar (Domzal and Unger, 1987). Hence, we assume that using the Global RepTrak® would not lead to a considerable bias in this study where we use data from the German website of Amazon.com. We used the brand specific RepTrak® scores that were up-to-date the time performance was measured.

4.1.2. Performance

Performance is the construct that product quality relates to. Prior research made a distinction between an objective and a perceived concept of product quality (e.g., Garvin, 1983; Holbrook and Corfman, 1985). While objective quality is defined as the "actual technical superiority or excellence of the products" (Zeithaml, 1988, p. 4), perceived quality reflects consumers' judgment about the products' features. However, it soon was recognized that objective quality can hardly be measured because the criteria which are used to do so and their weights are chosen subjectively (Zeithaml, 1988). Still, a distinction should be made between quality assessments that are mainly based on subjective feelings and experiences and those that are based on scientific and repeatable measurement methods. We refer to the latter as tested quality and use a correspondingly named indicator to measure performance.

More precisely, performance is measured using the grades of "Stiftung Warentest" (SW), a German customer magazine similar to "Consumer Reports" in the US. SW is a neutral organization founded by the German government in 1964. It is financed by selling test results online and in paper form and supported by the state (Stiftung Warentest, 2015). The organization's main objective is to test products and services using scientific methods. The test results of SW can be downloaded from a fee-based website. The grades represent an objective and mechanistic approach to evaluate products. The measurement is reliable since the outcomes of repeated product tests (even if carried out by different persons) would lead to the same results. The data for the single indicator *tested quality* was collected on the website of SW. We included all digital camera and television tests during a five year period from 2009 to 2014 to achieve a large overlap between the tested products and currently sold products on the German website of Amazon.com. The evaluation scheme of SW ranges from 1 = "very good" to 5 = "inadequate" and has been inverted before calculation. Overall product grades are the result of averaged sub category grades that can lie anywhere between the extremes, and are rounded to one decimal place. The distribution of SW grades in our sample is shown in Fig. 4.

4.1.3. Product rating

As discussed above, the customer feedback in online shops can be seen as the expression of their satisfaction with the product. Therefore, the dependent variable product rating was measured using the score of the individual star rating that a customer has

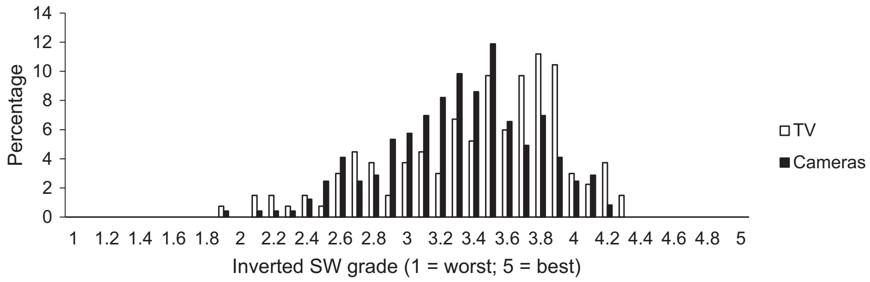

Fig. 4. Distribution of SW grades per product in the studies on cameras and televisions.

assigned to a specific product. We gathered the online rating data from the German website of Amazon.com, which is by far the largest online store in Germany (Statista, 2015). Other online stores were not taken into account to avoid biases caused by different qualities of retailers. Customers of Amazon.com are able to rate products on a five-star rating scale ranging from 1 = "I hate it" to 5 = "I love it" and additionally write customer reviews. We used a crawler to identify those products on Amazon.com that were tested from SW and downloaded all ratings and their timestamps. The camera data was collected on September 13, 2014 and the television data was collected on November 05, 2014.

Of the 1423 products tested by SW between 2009 and 2014, 56 percent have been identified on the Amazon.com website. 31 products were removed from the analysis because no online product ratings were available. Some reviews on Amazon.com are not uniquely associated with one product, but with several product types (e.g., a television model that is available with a 42 in. and 55 in. screen). In this case, one of the products was randomly selected following the procedure of Lim et al., (2010). Because of this, 62 items were removed so that all ratings are assigned to only one product. Additionally, we included only manufacturers of digital cameras and televisions that are in the RepTrak® 100. Overall, 378 products and 28,873 ratings were used for the calculation. Table 1 presents a detailed overview of the dataset and Figs. 5 and 6 illustrate the distribution of individual star ratings per customer and the average star rating per product on Amazon.com.

4.2. Data analysis and results

Structural equations were used to model the research model. Structural equation modelling (SEM) is a family of techniques that allow to model relationships between one or more independent variables and one or more dependent variables. Both independent and dependent variables can either be measured directly or indirectly (latent variables) (Ullman and Bentler, 2003). SEM differentiate between measurement models of (latent) variables and the relationships between the variables – the so-called structural model. Within the set of SEM techniques we chose the partial least squares (PLS) algorithm (cf. Chin, 1998) because it allowed us to handle single item measures (performance and product rating) and formatively measured latent constructs (expectation) simultaneously (Hair et al., 2013). Distributions of the indicators building a satisfaction construct are often heavily skewed (Fornell, 1992). The distribution of star ratings in the presented studies show a high skewness towards the higher ratings as well (see Fig. 5). PLS offers the advantage that non-normal distributions can be computed without manipulating the original data. Therefore, we used SmartPLS 3.2 (Ringle et al., 2015) to calculate the data. In a first step we evaluate the measurement model of the construct expectation and then assess the relationships of the research model.

Table 1
Dataset details.

Criterion	Cameras	Televisions	Total
Products tested by SW since 2009	885	538	1423
Products found on the German Amazon.com website	571	222	793
Products that were removed because they had no ratings	15	16	31
Products that were removed because of duplicate ratings	0	62	62
Products that were removed because of missing brand indices	312	10	322
Products used in the analysis	244	134	378
Product ratings used in the analysis	12,563	16,310	28,873

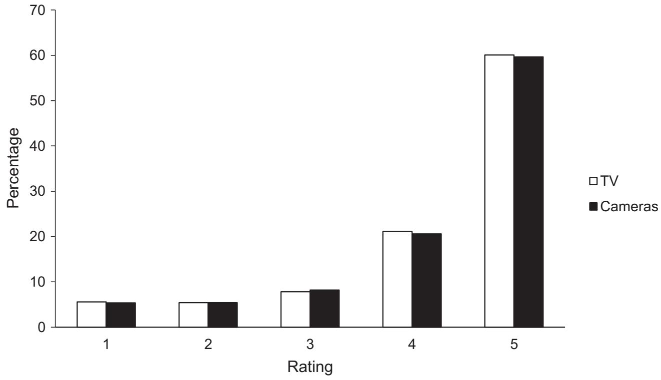

Fig. 5. Distribution of individual Amazon.com ratings in the studies on cameras and televisions.

4.2.1. Measurement models

The formative measurement model of the latent construct expectation was evaluated by looking at the indicator weights, their significance, and an assessment of multicollinearity (Hair et al., 2012). An overview of the results is given in Table 2. In the study on cameras all indicators significantly affect expectation in the theorized way. The variance inflation factor (VIF) score of 1.5 is well below the recommend upper limit of 5 and indicates a non-critical level of collinearity (Hair et al., 2013). The study on televisions shows mixed results. Only the indicator previous ratings has a positive and significant weight while the outer weight of price is insignificant and brand reputation is significant but negative. Nevertheless, we kept the indicators in the research model for two reasons. First, an elimination of insignificant indicators would affect the definition of the construct (Diamantopoulos and Winklhofer, 2001) and would lead to an incomparability between the two studies. Second, negatively weighted items should remain in the model if they are collinear and do not show reversed signs across studies (Cenfetelli and Bassellier, 2009).

4.2.2. Structural model

As shown in Table 3 and Table 4, we examined the path coefficients (β) and the level of significance for every hypothesized relationship as well as the explained variance (R^2) of the dependent variable for both studies. The path coefficients between expectation (CA: β=0.133; TV: β=0.202) and performance (CA: β=0.044; TV: β=0.024) on the one hand and satisfaction on the other hand are significant at $p < 0.001$ confirming H1 and H2 in both studies. Expectation consistently affects satisfaction considerably higher than performance. Although both hypotheses are strongly confirmed for cameras and television, expectation and performance explain 2.6% and 4.2% of the satisfaction variance respectively. We discuss the implications of these results in the next section.

5. Discussion

Comparing the distributions of ratings given to a product by SW (Fig. 4) and by customers (on average) (Fig. 6), we first note that product ratings do not reflect pure product quality since both distributions clearly differ from each other. This is consistent with prior research (Hu et al., 2006; Koh et al., 2010) and results, inter alia, from neglecting users' expectations, as elaborated on earlier.

When taking into account users' expectations an ambiguous conclusion can be drawn: On the one hand, H1 and H2 are confirmed by our data; that is, we find our research model to be suited for explaining online product ratings. As indicated by the text reviews, the rating score reflects the customer's expectation of the

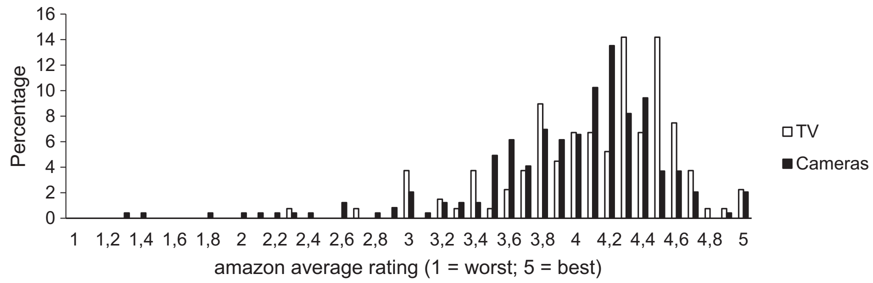

Fig. 6. Distribution of average Amazon.com ratings per product in the studies on cameras and televisions.

Table 2
Measurement model of the construct expectation.

	BR	PR	RP	EXP
Study CA (Camera)	0.154^{**}	0.423^{***}	0.745^{***}	1.429
Indicator weight				
VIF				
Study TV (Television)	-0.093^{*}	$-0.059^{n.s.}$	1.003^{***}	1.008
Indicator weight				
VIF				

* $p < 0.05$.
** $p < 0.01$
*** $p < 0.001$

Table 3
Statistics of dataset from study on digital cameras.

	r^2	Path coefficient (β)	*T*-value	*p*-value	Hypothesis confirmed
PRO	0.026				
EXP→PRO		0.133^{***}	13.121	$p < 0.0001$	H1: Yes
PER→PRO		0.044^{***}	4.412	$p < 0.0001$	H2: Yes

*** $p < 0.001$

Table 4
Statistics of dataset from study on televisions.

	r^2	Path coefficient (β)	*T*-value	*p*-value	Hypothesis confirmed
PRO	0.042				
EXP→PRO		0.202^{***}	24.700	$p < 0.0001$	H1: Yes
PER→PRO		0.024^{***}	3.806	$p < 0.0001$	H2: Yes

*** $p < 0.001$

product and an assessment of product quality. In contrast to the prevailing opinion, we find ratings to be even more influenced by expectation than product quality.

On the other hand, however, the explained variance is relatively low in both studies. This can be assumed to have three causes: First, a particular customer's satisfaction with the product he has purchased is likely to depend on the expectation and performance of his specific needs (e.g., a long lasting battery). These needs are not observed in our study. The drawback of measuring performance by the product's quality (i.e., on product-level) is that we cannot break down the performance to each of its characteristics. Second, the presence of high fake ratings significantly diminishes explained variances: since a fake rating does neither depend on customer expectation nor on product performance, the corresponding observation cannot be explained by our model. Thus, the percentage of variance explained can be expected to be much higher if no fake ratings are present. In contrast, it should be noted that the general results are not affected by fake ratings because their frequency distribution can be assumed to be uncorrelated with the indicators used. Third, we argue that reviews exhibit a high degree of "randomness" by nature. This result, which might seem intuitive at a first glance, has an important implication: if individual ratings could be explained by any model to a high degree, they would become superfluous. A rating that can be accurately predicted cannot contain any new information.

The same applies if ratings are rather determined by observable factors than by raters' experiences. Indeed, we find them to be significantly influenced by a product's price and the reputation of its manufacturer consistent with results of prior research (Dodds et al., 1991). Furthermore, our results provide evidence for social dynamics as described in Moe and Trusov (2011). Customers base their evaluations rather on previous ratings than on their individual experience. The weight of the previous ratings' score is even greater than the weights of the other indicators, suggesting that social dynamics have a stronger influence on customers than price or brand effects.

We also find signs for biases during the rating process. First, the product rating distribution is highly skewed. This is often attributed to under-reporting bias (Anderson, 1998): customers with extreme values of satisfaction (very low or very high) are more likely to review a product than customers with mean levels. Interestingly, however, the distribution is negatively skewed, that is, high ratings are much more prominent than low ratings. This may have two reasons. First, it could result from the so-called acquisition bias (Hu et al., 2006): only users who have a sufficiently high expectation of a product will consider purchasing it. Second, it is known that a certain amount of ratings are fake (e.g., ca. 16% at yelp.com, (Luca and Zervas, 2013)). They are created by or on behalf of manufacturers and retailers to increase the average ratings and, hence, the sales of their products. This effect spans a stream of research of its own (e.g., Malbon, 2013; Lappas et al., 2012; Mukherjee et al., 2012). We find no indications for the reverse effect, that is, fake reviews given to products by competitors in order to decrease their average rating.

Finally, we find that customer satisfaction is more affected by expectation than by performance. In addition to the hypothesized belief-adjustment mechanism underlying the relationship between expectation and rating, this might also indicate a confirmation bias (cf. Nickerson, 1998). Customers tend to interpret evidence in favor of their prior expectations about the product instead of evaluating the product they have purchased objectively – they see what they like to see. This also relates to the theory of cognitive dissonances (Festinger, 1962). If the product does not meet their expectations, a cognitive dissonance between expectation and performance occurs. Our results suggest that customers rather resolve this dissonance by mitigating the product's deficiencies than by revising their expectations.

6. Implications, limitations, and conclusion

In this study, we have shown that the customer satisfaction model of online product ratings is better suited to explain the score of ratings than traditional quality-centered explanations. This means that customers' ratings of products depend on their expectation about these products and their performance. This finding has rich and concrete implications for both research and practice.

The development and empirical test of this model advances theoretical knowledge by introducing the customers' expectation as a determinant of online ratings. Thereby, we refine the current understanding of the baseline of online ratings. The empirical results suggest that the model provides a valuable tool to analyze online ratings and is a valid starting point to elaborate on biases more accurately.

Without the insights of this study, practitioners in retailing and manufacturing may draw erroneous conclusions for marketing decisions based on existing reviews if they rely on the invalid assumption that online product ratings reflect true quality. To counteract this, rating mechanisms have to be optimized. We recommend establishing a rating system that allows users to input their individual expectations of specific products. This way, products can be ranked according to a rating based on the confirmation of expectations. For example, a user who wants to take a few snapshots has other expectations towards a digital camera than a professional photographer. When considering solely the rating score, both camera types might look like they were recommended for both user types but the camera for beginners will most certainly not meet the expectations of professional photographers and vice versa. The problem is that the different expectations are not accounted for by current rating systems based on a single rating value. Even current multi-criteria rating systems (as used, e.g., on ebay.com), which allow ratings for several criteria (e.g., robustness) of a product are not suited for this approach. This is because expectations may relate to several criteria simultaneously (e.g., quality and support). By assessing expectations and the degree of fulfilment separately, manufacturers can learn about users' expectations of their own and competing products which enables them to develop better marketing strategies. On the other hand, they can deduce how satisfied their customers are with the degree to which these expectations are met which enables better product designs. Furthermore, the accuracy rate of recommender systems can be improved this way. If retailers know the customer's expectation of a product, they can suggest further potentially interesting products with similar expectation values.

As every empirical work, our paper is not free of limitations. First, we have analyzed online ratings without considering the textual reviews accompanying them to test the theory. Prior research (Chevalier and Mayzlin, 2006) has shown that these reviews carry information that adds up to the information carried by the ratings. Furthermore, some websites offer their users the possibility to rate customer reviews in order to determine their helpfulness (Mudambi and Schuff, 2010). These second-order ratings were not considered in this study to emphasize the theorized hypotheses. Future research can validate our results by including these additional data. Second, crawled data were chosen to evaluate this exploratory research model. On the hand side, this approach increases the external validity but one the other hand, it limits internal validity. To contradict this issue, survey-based research measurement of expectation should be employed in addition to crawled data in future research. Third, we focused a single marketplace and two groups of tech products to avoid biases caused by different shopping experiences. Future research can, therefore, examine different marketplaces or products from different categories such as experience goods.

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Essay VI

Titel

Contribution and Consumption of Content in Enterprise Social Media

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Contribution and Consumption of Content in Enterprise Social Media

Abstract

The popularity of social media for private use and the potential benefits of their use within enterprises have led many companies to participate in public social media and to implement such software for internal use. This paper focuses on the adoption of social media for internal use only. So, while many enterprises adopted it as an organization, the question remains whether individual employees adopt it, too, and if so, how they (intend to) use it. We distinguish two major types of use: content contribution and content consumption. Both types of use are modeled based on an adapted technology adoption model and tested within a big company. The general results show that the intent to contribute content can be well predicted with this approach but not the intent to consume content. One of the specific results is the observation that social influence, often more or less soft pressure to use enterprise social media, does not work in the case of content consumption. Given that these users expect to improve their performance through enterprise social media just like content contributors, according to our research, such use should be better promoted and planned.

1. Introduction

Social media such as blogs, wikis, and social networks have first become popular in the private realm and then, they found their way into corporate intranets. Enterprises have realized that they may benefit from employees who contribute and consume content across formal organizational structures (e.g., in terms of higher productivity and more collaboration) within enterprise social media (ESM) (Alfaro, Bhattacharyya, & Watson-Manheim, 2013; Bughin & Chui, 2010; McAfee, 2006). Therefore, they increasingly adopt ESM. However, organizational adoption does not guarantee individual adoption by employees (Agarwal & Prasad, 1997) when software use is not mandatory. The use of ESM is usually voluntary because it is not employed for daily transactions such as enterprise resource planning systems but to support less structured, knowledge-based tasks (e.g., collaboration, idea generation, or knowledge preservation). This means that although an organization implements ESM, the organization members decide on the type and extent of use.

This implies that not every employee will join the ESM community, and of those who join, not everyone will contribute content. Although content sharing is the cornerstone of every ESM community (it is what ESM are designed to help users to do), users who only consume content (so-called lurkers) are the large majority (Alpar & Blaschke, 2011; Ebner, Kickmeier-Rust, & Holzinger, 2008; Muller, Shami, Millen, & Feinberg, 2010). While content consumption without contribution does not help to grow content on the ESM platform, it can help employees to grow their knowledge, transfer it, and apply it in their day-to-day work outside ESM. Since both usage types can be valuable for enterprises, the challenge of research examining the use of ESM is to account for both, the necessary content contribution and the invisible but more frequent content consumption.

So far, most analyses focus on the role of content-creators (e.g., Engler, Alpar, & Fayzimurodova, 2015). The determinants of content consumption on ESM remain unclear and, hence, a comparison between the drivers of contribution and consumption is not possible. Traditional technology acceptance research (e.g., using the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT)) generally relies on one dependent variable commonly called use or intention to use. It might be legitimate to ask if an employee uses the software because use is not ambiguous when examining standard software. However, when asking someone if he uses ESM, employees may refer to the same software but to completely different types of use (contribution or consumption).

Therefore, the objectives of this paper are to uncover the determinants of ESM adoption for the two types of use and analyze whether antecedents differ. Further, we examine whether a traditional technology acceptance model developed before the rise of social media can still be used in the context of corporate ESM. Thus, the following research questions are addressed in particular:

(1) What drives content contribution and content consumption on ESM?
(2) Are there any differences between the predictors of contribution and consumption?
(3) Are traditional technology acceptance models capable of predicting fundamentally different types of use?

To answer these questions, we develop a theoretical framework based on the UTAUT model with two separate dependent variables and test the suggested model using PLS structural equation modeling to analyze survey data collected in a multinational information, communication, and technology (ICT) company. Thereby, we start with a proven approach to put a focus on potential similarities and differences between content contribution and consumption but also deviate from it by testing for two separate dependent variables.

The paper is organized as follows: in the next section, we introduce ESM and elaborate on the difference between content originators and consumers (also lurkers). Then, we develop the hypotheses to formulate the research model. In the fourth section, we describe the research methodology, the data collection procedure, and present the study's results. Finally, we discuss the results, derive theoretical and practical implications and conclude with a brief summary.

2. Background

2.1 Enterprise social media

The terms social software and social media are synonymous for "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of User Generated Content" (Kaplan & Haenlein, 2010, p. 61). They can be, therefore, considered as a subset of Web 2.0. The use of social media in corporate intranets is referred to as enterprise 2.0 (McAfee, 2006) and the software as ESM (e.g., Brzozowski, Sandholm, & Hogg, 2009). ESM allows employees, inter alia, to communicate with one or many coworker(s), to reveal personal networks, to jointly create/edit files and share them, and to view everything aforementioned at any given time (Leonardi, Huysman, & Steinfield, 2013). ESM can include blogs, social networks, wikis, social news, prediction markets, and some other applications. We concentrate here on the first three. Blogs are web pages which are updated regularly. Their content appears in a reverse chronological order and can consist of text, pictures, videos, or sounds (OECD, 2007). Social networks are applications that allow users to set up profiles in closed systems, to create a list of contacts, view the contact lists of other users, and interact (Boyd & Ellison, 2007). Beyond that, they offer additional services to increase the communication between members like built-in chats, blogging and mailing services, and platforms for sharing various multimedia contents. Wikis are web-based applications consisting of linked sub-sites which are jointly created within this application by a community of users (Leuf & Cunningham, 2008).

2.2 Content contribution and consumption

A growing body of work examines the use of ESM in knowledge management by focusing on selected software such as blogs or wikis (e.g., Raeth & Smolnik, 2010; Wagner, 2004) or processes such as information retrieval (e.g., Alpar, Engler, & Schulz, 2015; Engler, 2014) and content contribution (Engler et al., 2015). Additionally, various determinants that influence knowledge sharing in ESM have been researched in extant literature: trust (Chai & Kim, 2010), organizational climate (Kügler, Lübbert, & Smolnik, 2015), gender (Chai, Das, & Rao, 2011), and factors related to social capital (Chiu, Hsu, & Wang, 2006). However, knowledge seeking and retrieval are actively intended behaviors to fulfil certain goals, while news feeds and timelines in ESM deliver new content even without the employee requesting it. Furthermore, the mentioned studies incorporate one single dependent variable relating to use applying different theoretical frameworks. On this basis, a comparison of content contribution and consumption is not possible. A first step to account for potential differences and focus specifically on two separate variables was done by Schöndienst et al. (2011). They partially adapted UTAUT and found intention to contribute to be negatively influenced by privacy concerns and driven by performance expectancy. The intention to follow users in an enterprise micro-blogging system was positively affected solely by the users' performance expectancy. Further qualitative research identifies the following main motivations to lurk on Internet communities: wish for anonymity, work related constraints prevent from posting, entertainment (Nonnecke & Preece, 2003), feeling that one is not helpful, poor group fit, no requirement to post, and learning about the group (Preece, Nonnecke, & Andrews, 2004). Besides that, little is known about the motives underlying the lurking phenomena in enterprises.

3. Hypothesis development and research model

Unlike unidirectional media technologies such as print media or television, collaboration technologies are based on a bidirectional principle. Users can be both producers and consumers of information, so-called "prosumers" (Toffler, 1980). While using social media applications, users have the choice to create blog posts, make comments, create wiki articles, change them, create friends lists on social networking sites, post their photos there, or to act passive and be content with consuming content. Users can, therefore, be classified as content contributors and content consumers. Hence, we suggest a combination of traditional technology acceptance research with its high explanatory power and a segmentation of the dependent variable into two dimensions: content contribution and content consumption.

3.1 Content contribution

Venkatesh et al. (2003) conducted an overview and an empirical comparison between eight extant models in the field of IT acceptance research and combined four core constructs to formulate the unified theory of acceptance and use of technology. UTAUT draws a comprehensive picture of the technology adoption process and explains in a longitudinal study a higher proportion of the variance of behavioral intention and usage than each of the original acceptance models individually (Venkatesh et al., 2003). Hence, it provides a valuable tool for researchers and practitioners to understand drivers of adoption of information systems. According to UTAUT the independent variables performance expectancy, effort expectancy, and social influence determine behavioral intention. The dependent variable use behavior is subsequently predicted by facilitating conditions and behavioral intention (see figure 1). These relationships are moderated by gender, age, experience, and voluntariness of use.

Performance expectancy describes the degree of individually expected productivity improvements which are supported by the technology used. The variable effort expectancy (which is also referred to as perceived ease of use (Davis, 1989)) measures the extent of effort, which is deemed necessary to use the technology. Note that high effort expectancy means in the following high ease of use and not high effort to adapt the terminology of UTAUT. Social influence describes the individual perception regarding the relevance of other important persons' opinion on the target technology. Finally, facilitating conditions represent the ability to perform a behavior and contain the availability of support as well as organizational and technical prerequisites for the behavior (Venkatesh et al., 2003).

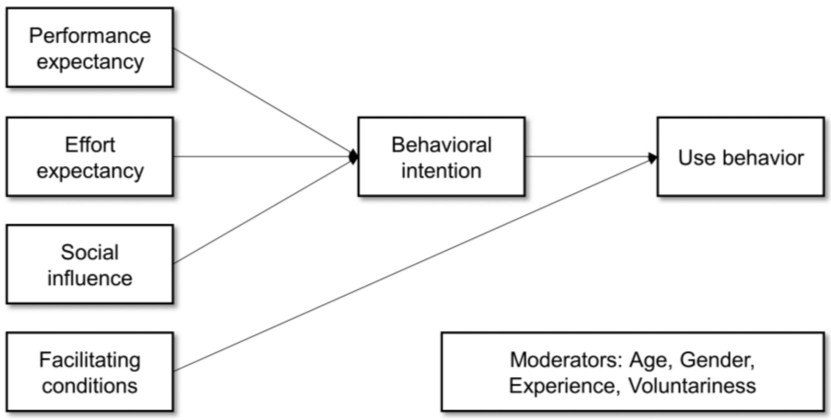

Figure 1. UTAUT research model (Venkatesh et al., 2003).

The dependent variable use behavior is not implemented in this study's research model because of possible incorrect inferences resulting from the early stage of social media use in enterprises (cf. Wang, Gwebu, Shanker, & Troutt, 2009). Thus, we do not investigate the relationship of facilitating conditions and technology use. Due to the importance of facilitating conditions, we apply a slightly different operationalization of the model instead. The initial relationship is replaced by a connection between facilitating conditions and behavioral intention as can be found in the theory of planned behavior (Ajzen, 1991). There, the construct perceived behavioral control (including its core component facilitating conditions) is linked to the behavioral intention analogously to the presented research model. This means that facilitating conditions such as organizational and technical support not only directly influence use behavior but also influence the behavioral intention.

In general, behavioral intentions are assumed to be a container of motivational factors (in this study captured by performance expectancy, effort expectancy and social influence) influencing the behavior (Ajzen, 1991). However, if an employee does not have the facilitating conditions to use the technology, motivational factors cannot contribute to increase usage. In case employees can accurately predict the degree of facilitating conditions, it is very likely that they also influence the initial behavioral intention. This is the case for ESM since the use of social media in the private realm is widely spread and, therefore, the resources needed are foreseeable.

Transferring the UTAUT hypotheses (including the change of the effect of facilitating conditions) to the research context leads to the following four baseline hypotheses describing the holistic use (contribution and consumption) of ESM.

Hypothesis H1: The higher the expected performance of ESM is, the higher is the intention to contribute content.

Hypothesis H2: The higher the effort expectancy of ESM is, the higher is the intention to contribute content.

Hypothesis H3: The more favorable the perception of use desirability (social influence) is, the higher is the employee's intention to contribute content.

Hypothesis H4: The stronger the perception of adequate facilitating conditions with regard to ESM is, the higher is the intention to contribute content.

3.2 Content consumption

Lurking on the Internet commonly has a strong negative connotation. Lurkers take information from a shared platform without developing the online community further by contributing content (Muller et al., 2010). On the intranet things change completely since the online community is also a subset of the community of employees of one company. Although individual goals may vary, all employees are working towards the same organizational goals. Processing information without contributing can, therefore, be a high performance, easy to use, socially supported, and resource-saving way to work towards the common objectives. In the following we argue why the four baseline hypothesis also hold for the pure consumption of content. The complete research model is shown in figure 2.

Without a critical mass of employees who contribute content limiting one's own use to just consuming content cannot be valuable (Markus, 1987). However, once this knowledge base has been built by content contributors, lurking can have the same benefits as searching for information in traditional, centralized, and structured knowledge repositories. As described above, lurking can have manifold motivations. The fact that an employee does not have anything significantly new or important to contribute does not exclude that s/he is able to transfer the information found in ESM to a beneficial output outside the scope of the software (Takahashi, Fujimoto, & Yamasaki, 2003). Although a lurking employee does not publicly seek for assistance or does not jointly create a solution, s/he can benefit this way from the questions and solutions contributed by fellow colleagues. This leads to the following hypothesis:

Hypothesis H5: The higher the expected performance of ESM is, the higher is the intention to consume content.

Setting up a profile page in an enterprise social network and entering the minimum required personal data take very little time and effort and some applications do not even require a registration to be able to consume content (e.g., blogs and wikis). However, consuming content from ESM is not free of effort. Besides the time that has to be spent to read posts or watch videos, search costs can be regarded as one major source that causes additional effort to consume content. Whereas wikis are highly structured and easily searchable, finding relevant content on internal social networks and in an intranet blogosphere can be different. Information is decentralized and might be spread over various profile pages and blogs (von Krogh, 2012). Once relevant information is identified, it takes additional effort to verify the information quality which is especially crucial in the corporate realm (Engler, 2014). Lowering the effort of searching and verifying content can, therefore, contribute to an increase of the willingness to consume content in ESM. Hence, we hypothesize:

Hypothesis H6: The higher the effort expectancy to use ESM is, the higher is the intention to consume content.

As described above, lurkers can attain job-related benefits without spending too much time and effort to contribute content themselves. This in turn should lead other organization members to support lurking as a valuable behavior. Superiors can thereby encourage employees to benefit from the workforce's knowledge without fearing that employees start chatting about non work related issues and wasting working time (Turban, Bolloju, & Liang, 2011). Similar motivations to encourage lurking are conceivable for peers (Skeels & Grudin, 2009). Since lurkers do not harm others by following public content, peers can regard lurking as a good way to retrieve information or a starting point for the future contribution of own content. This endorsement of the social environment at the workplace leads to a pressure to exhibit this behavior. Therefore,

Hypothesis H7: The more favorable the perception of use desirability (social influence) is, the higher is the intention to consume content.

Whereas performance, effort, and social influence represent motivational factors, facilitating conditions can be classified as a hygiene factor (cf. Herzberg, 1987). Even if employees are convinced that using ESM is beneficial, requires only minimum effort, and the peer group endorses this behavior, they can hardly intend to use the applications without the necessary resources such as the know-how and technical support. This also holds (albeit to a lesser extent) for their content consumption. Employees do not have to know how to codify knowledge to create a blog post or a wiki article but they must be able to access the platforms (with appropriate software and hardware) and have to know how to find the content they are looking for. Thus,

Hypothesis H8: The stronger the perception of adequate facilitating conditions with regard to ESM is, the higher is the intention to consume content.

3.3 Contribution vs. consumption

As described above, we expect the relationships between the independent and both dependent variables to have the same direction. However, we assume the strength of the relationships to be different. First, if an employee is convinced that the use of ESM increases his/her performance, it is very likely that s/he will try to lever the full potential of the software (Preece et al., 2004). This includes, for example, asking questions, jointly creating documents, and participating in discussion – in other words: content contribution and consumption. Second, if the employee perceives ESM to be easy to use it lowers not only the effort of use but also the threshold to initially use the software (Engler et al., 2015). Since contributing content requires clearly more time and effort than simply lurking, the leverage effect of the aforementioned mechanisms are higher in an easy to use system. Third, although lurking can be regarded as an overall valuable behavior, it is beneficial for the individual lurker in the first place. Lurkers may apply and spread their newly gained knowledge offline but do not help to further develop the community online. Since one of the main motivations underlying knowledge contribution in ESM is the wish for reciprocity (Engler et al., 2015), we assume the social environment to endorse contribution more than content consumption. Finally, following the line of arguments concerning effort expectancy, the presence of facilitating condition weigh heavier if the use of the software is more complex (requires more resources) as it is for knowledge contributors. Summarizing the above, we hypothesize:

Hypothesis H9: The influences of (a) performance expectancy, (b) effort expectancy, (c) social influence, and (d) facilitating conditions on intention to contribute content are stronger than their influences on the intention to consume content.

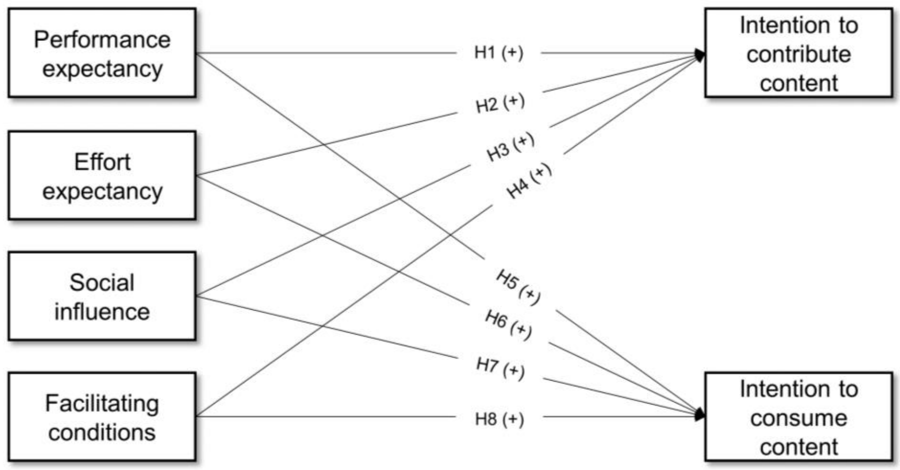

Figure 2. Research Model.

4. Research method and data analysis

4.1 Measurement and data collection

The empirical investigation of the research model via structural equation modelling requires an operationalization of the theoretical constructs using appropriate measurement models. Apart from the choice of suitable items, the direction of causality in the measurement models has to be considered (reflective or formative). Already proven and reliable scales were drawn from prior research (see appendix A). The scales of performance expectancy, effort expectancy, social influence, intention to contribute and intention to consume content are based on Venkatesh et al. (2003) and have been modelled as reflective constructs following the approach in their study. However, we argue that the measurement model of facilitating conditions should be formatively measured for the following reasons: the direction of causality is from the items to the construct, the items are not interchangeable, covariation among the items is not necessarily given, and they do not have the same antecedents. Hence, it fits all criteria of a formative measurement model according to Jarvis et al. (2003). All items of the measurement models were measured on a seven-point Likert scale with the anchors being "strongly disagree" and "strongly agree".

We conducted a field study in German locations of an international ICT company right before the implementation of an organization-wide social media platform. Before, ESM was sparsely used by some work groups deploying heterogeneous applications and without official corporate backing. Empirical data shows that large companies within this branch are usually found among the early adopters of ESM (Leibhammer & Weber, 2008; Saldanha & Krishnan, 2012). To verify the research model empirically, an online-based, self-administered survey was used to reach employees at several locations and in different business units. A total of 217 employees completed the online survey (at 382 page views). The data set has been inspected for completeness, systematic outliers, processing time, and frequency distribution of answers to ensure high quality data. 29 records were excluded for these reasons. In the final sample of 188 responses, 42.55 percent were female, 51.06 percent were male and 6.38 percent made no statement on gender. At the time of the survey the youngest participant was 20 years of age while the oldest one was 59 years old. The average age was 35.52 years (SD = 9.24). Age and gender distributions correspond with those in the whole company which means that no non-response bias with respect to these variables occurred. They are also not significantly different between early and late respondents.

4.2 Data analysis

Partial least squares (PLS) (cf. Chin, 1998) was used to analyze the data because it allows to simultaneously compute formative and reflective measurement models, is less demanding regarding sample size and the distribution of data, and is generally recommended for sample sizes smaller than 250 (Reinartz, Haenlein, & Henseler, 2009; Streukens, Wetzels, Daryanto, & de Ruyter, 2010). We used the software SmartPLS 3.2 (Ringle, Wende, & Becker, 2015) to calculate the model. In a first step, we evaluate the measurement models and then look at the relationships between the constructs of the structural model. The significance tests are performed using t-values from the bias corrected and accelerated bootstrapping procedure, with 5000 resamples.

4.2.1 Measurement Model

The criteria indicator reliability, composite reliability, convergent, and discriminant validity were assessed to evaluate the quality of the reflective measurement models (Hair, Hult, Ringle, & Sarstedt, 2013). The formatively measured construct is assessed with regard to item multicollinearity, indicator weights, and their level of significance.

Indicator reliability can be assessed by looking at the indicator loadings. The loadings should surpass a threshold of 0.7 to indicate sufficient reliability. All but one item fulfilled this criterion in the first calculation. Item 1 of effort expectancy revealed a lower outer loading and was dropped consequently. In the second calculation (excluding item 1 of EFEX) the indicator reliability was sufficient as indicated in table 1. Composite reliability was evaluated using internal consistency reliability (ICR). ICR uses weighted item loadings and is therefore considered a better reliability measure than Cronbach's alpha for structural equation models (Chin & Gopal, 1995; Fornell & Larcker, 1981). All reflective variables show ICR values above 0.9, thereby exceeding the recommended lower limit of 0.7 (Nunnally & Bernstein, 1994). We checked for convergent validity by calculating the average variance extracted (AVE) by a measure. A value above 0.5 is considered acceptable (Fornell & Larcker, 1981) and fulfilled for all constructs as shown in table 1.

	Indicator loadings / *weights*			**Average Variance Extracted**	**Composite Reliability (ICR) / *VIF***
	Item 1	**Item 2**	**Item 3**		
PEEX	0.839	0.916	0.924	0.799	0.922
EFEX	dropped	0.921	0.965	0.889	0.941
SOIN	0.927	0.913	0.769	0.761	0.905
FACO	*0.108*	*0.658****	*0.514****		*1.444*
CONT	0.934	0.947	0.933	0.880	0.957
CONS	0.937	0.930	0.948	0.881	0.957

Note: *** = $p < 0.001$

Table 1. Measurement model assessment.

Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981). It states that the square root of the AVE (shown in the shaded fields in table 2) should be greater than the correlation of the construct with any other construct in the research model. The results in table 2 meet the criterion and thereby confirm discriminant validity in our data.

	Average score	PEEX	EFEX	SOIN	FACO	CONT	CONS
PEEX	4.658	0.894					
EFEX	5.093	0.504	0.943				
SOIN	3.721	0.444	0.236	0.872			
FACO	4.727	0.432	0.423	0.422	n.a.		
CONT	4.400	0.641	0.374	0.435	0.505	0.938	
CONS	4.941	0.326	0.201	0.087	0.290	0.251	0.938

Table 2. Average variable scores, correlations between constructs, Fornell-Larcker criterion.

The items 2 and 3 of the formatively measured construct *facilitating conditions* show positive indicator weights and are significant on a 0.1% level. Even though item 1 has no significant outer weight, we kept it in the measurement model because of its theoretical relevance for the construct's definition (cf. Cenfetelli & Bassellier, 2009). Finally, its indicators were checked for multicollinearity by assessing the variance inflation factor (VIF). The resulting VIF value of 1.444 lies well below the recommend upper limit of 10 (Reinartz et al., 2009) and indicates low multicollinearity.

We checked the data for common method bias using Harman's single-factor test because all latent constructs were measured using survey data. A substantial amount of common method variance would be indicated, if a single factor would explain the majority of the variance of all measured variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). In this study, a single factor explains at most 36.3 % of the variance which indicates that common method bias is not an issue.

4.2.2 Structural Model

With the measurement models being reliable and valid, we assessed the relationships between the latent variables. As shown in table 3 we found that all but one hypotheses concerning the content contribution are confirmed. Only effort expectancy was not found to significantly influence content contribution. Therefore, hypotheses H1, H2, and H4 are confirmed.

However, only performance expectancy and facilitating conditions were found to be significant positive predictors of content consumption (supporting H5 and H8). Effort expectancy does not have a significant influence on content consumption and social influence even show a negative significant effect on content consumption.

The model explains 48.5% of the variance of intention to contribute content and 14.7% of the variance of intention to consume content.

Path	Path coefficient	t Value	p Value	Hypothesis confirmed?
PEEX → CONT	0.484***	6.750	p < 0.000	H1: Yes
EFEX → CONT	-0.002	0.059	p < 0.477	H2: No
SOIN → CONT	0.115*	2.017	p < 0.022	H3: Yes
FACO → CONT	0.249***	3.481	p < 0.000	H4: Yes
PEEX → CONS	0.295**	3.249	p < 0.001	H5: Yes
EFEX → CONS	-0.011	0.208	p < 0.418	H6: No
SOIN → CONS	-0.137*	1.714	p < 0.043	H7: No
FACO → CONS	0.225**	2.479	p < 0.007	H8: Yes

Note: *** = p < 0.001; ** = p < 0.01; * = p < 0.05

Table 3. Results of PLS analysis.

Additionally, we calculated the path differences between every independent variables influence on intention to contribute and intention to consume content and assessed the significance of the difference using the parametric approach outlined in Hair et al. (2013). In general, all path coefficients between the independent variables and intention to contribute content are higher than their coefficients on intention to consume content (see table 4). Whereas the influences of performance expectancy and social influence on intention to contribute are significantly higher than on intention to consume content supporting the hypotheses 9(a) and 9(c), the relationships of effort expectancy and facilitating conditions on intention to contribute (respectively consume) content are not significantly different.

Independent variable	Dependent variable		I β CONT – β CONS I	t Value	p Value
	β CONT	β CONS			
PEEX	0.484	0.295	0.189*	1.655	p < 0.049
EFEX	-0.002	-0.011	0.009	0.143	p < 0.443
SOIN	0.115*	-0.137	0.252**	2.578	p < 0.005
FACO	0.249	0.225	0.024	0.207	p < 0.418

Note: β CONT and β CONS are path coefficients of the respective independent variable on the intention to contribute/consume content; ** = p < 0.01; * = p < 0.05

Table 4. Path differences.

5. Discussion

5.1 Baseline model (content contribution)

The findings of the baseline model containing hypotheses on content contribution provide a strong support for the proposed adaptation of UTAUT to the research context. The model explains a huge amount of variance (48.5%) and lies in some cases well above established models with a focus on knowledge sharing (e.g., Bock, Zmud, Kim, & Lee, 2005; Wasko & Faraj, 2005). The supported hypotheses H1, H3, and H4 reconfirm that performance expectancy, social influence, and facilitating conditions are key drivers for technology acceptance. However, these findings not only echo the results of prior technology acceptance research using UTAUT but also offer interesting insights into characteristic phenomena of ESM.

Notably, performance expectancy is by far the strongest predictor of intention to contribute content. While the construct is among the most important drivers of adoption across technologies (Venkatesh et al., 2003), it is surprising that the contribution of content in ESM, whose uses might be emergent and initially undefined, is primarily driven by the wish for an improved performance. In contrast to this finding, the use of social media in the private realm is not significantly influenced by its purposive value but rather primarily driven by the ability to pass time (Cheung, Chiu, & Lee, 2011). This also emphasizes the difference between the use of social media on the Internet and ESM and the resulting need for a separate consideration.

In contrast to the original UTAUT but in accordance with recent literature (e.g., Parra-López, Bulchand-Gidumal, Gutiérrez-Taño, & Díaz-Armas, 2011), no significant relationship between effort expectancy and intention to contribute content was found. On the one hand, this might be caused by the ever growing IT-savviness of nowadays users (He & Wei, 2009). On the other hand, social media are omnipresent in the everyday private life of many employees. Experience gained with privately used social networks or searching for information on Wikipedia.org can be transferred to ESM lowering the importance of an easy to use system.

5.2 Content consumption

In contrast to the strong support for the model on content contribution, we obtained mixed results for the examination of content consumption. While a high performance expectancy and the presence of facilitating conditions foster the intention to consume content, the relationship between effort expectancy and intention to consume content is again insignificant and the influence of social influence works exactly the other way around in comparison to hypothesis H7.

The strong effect of performance expectancy and the weak and insignificant effect of effort expectancy on the intention to consume content correspond with the findings of the baseline model. While the first result supports the value of consuming content from ESM, the insignificance of effort expectancy contradicts the commonly held notion that lurkers are free-riders who are not willing to make a contribution to the community since it requires too much effort (cf. Kollock & Smith, 1996). Our results suggest that employees want to consume content because they expect performance gains (e.g., by meeting their information needs (cf. Nonnecke & Preece, 2001)) rather than because it demands less effort. It must be noted, as hypothesized, performance expectancy has a significantly higher effect on intention to contribute than on intention to consume content which suggests that employees who expect a performance benefit indeed prefer to lever the full potential of ESM. Nevertheless, the significantly positive performance expectation strongly supports the view that lurking is a strategic activity and not an act of selfish free-riding (Preece et al., 2004) and it helps to complete the picture of an active lurker drawn by Takahashi et al. (2003).

While we found content consumption to be primarily driven by the wish for an increased performance, we found the social environment at the workplace (peers and superiors) does not support lurking but prevents it. The more the peer group endorses using ESM, the lesser is the intention to use ESM by lurking. This may look like a desirable behavior at the first glance. However, it involves the inherent risk that employees end up refusing the whole system rather than trying to contribute. Especially when facing the high percentage of content consuming users (in our study, 144 out of 188 participants reported a higher average score for content consumption than for contribution), this well-meant social influence has the potential to prevent the ESM community from natural growth. The significant difference of social influence on content contribution and content consumption reconfirms that the perception of lurkers as free-riders who are not beneficial to community development still remains the predominant opinion of colleagues and superiors. Conversely, our results regarding the performance expectancy allow the opposite conclusion. Furthermore, the difference emphasizes the strong wish for reciprocal support in ESM found in previous research (Engler et al., 2015).

Although the lack of empirical investigations of antecedents to lurking prevents a qualitative assessment of explained variance, the R-squared value of 14.7% in the content consumption setting can be classified as low. Looking at the baseline model, it must be noted, that the explanatory power of UTAUT's independent variables strongly differs between two different uses of one software. While the contribution in the baseline model is sufficiently explained, it becomes apparent that important factors determining the intention to consume content are missing in the model. While our research model was designed to directly compare posting and lurking, more specific determinants should be incorporated when aiming for a higher explained variance of the lurking behavior.

5.3 Limitations and future research

Prior to elaborating on the implications of this study, it is necessary to note that the research design is not free of limitations. First, the data was collected within several locations of one company. With the focus of this research lying on the differences between content consumption and contribution, we aimed for ruling out biases caused by different ESM platforms or enterprise cultures. However, this approach limits the generalizability since we cannot ensure external validity. Future studies can replicate the study across cultures and enterprises to generalize the results. Second, the completion of the questionnaire was voluntary and, hence, a self-selection bias may have occurred (Stanton, 1998). Since we found that age and gender distributions in the study are very similar to their distributions across the firm, we assume that self-selection is not a major issue with regard to the demographics. Finally, due to strict data privacy policies and employee rights it was not possible to track actual use behavior in the post-implementation phase and to tie it to our data set. Since behavioral intention does not necessarily always correlate with system usage (Wu & Du, 2012), future research would benefit from supplementing this study from the pre-implementation phase with a longitudinal approach that uncovers relationships between the dependent variables and actual posting and reading behavior.

5.4 Implications for theory and practice

A deep understanding of technological and individual determinants influencing the technology adoption process is currently one of the most mature streams in research on information systems (Benbasat & Barki, 2007; Venkatesh, Davis, & Morris, 2007). This study seeks to advance knowledge within this stream with an important contribution: while traditional technology acceptance research (e.g., UTAUT) is well-suited to research technologies where there is only one main type of use, it reaches its limits when it comes to fundamentally different uses such as in ESM. The advantage of using a single, parsimonious, and proven approach for both dependent variables lies in the fact, that we could reveal valuable insights about path differences. Thereby, we are able to show the necessity of two separate dependent variables. Focusing on a single type of use either ignores the small but very important group of community-building contributors or the by far larger group of lurking employees. Starting with the conjured dawn of emergent collaboration (McAfee, 2006), ESM with various and diverse uses made the leap into enterprises. The results of this study suggest that researching this class of enterprise software without being very precise when choosing the dependent variable can lead to fatal misinterpretations. Instead, future research should rely on frameworks specific to the type of use.

For practitioners, the study has concrete implications. The observed discrepancy between the strong effect of performance expectancy on intention to consume on the one hand and the negative social influence on the other hand reveals the most valuable starting point. Instead of endorsing only content contribution, managers should abandon the general notion that lurkers are free-riders and endorse content consumption as a valuable behavior. This way, the huge percentage of lurkers can be better motivated to use the software without feeling that they are doing something that is socially not valued. They can disseminate the information gained through different channels and even contribute to knowledge growth in other settings. It still needs to be determined how to measure this impact of using ESM.

Furthermore, the insignificance of effort expectancy in both scenarios indicates that ESM have reached a satisfactory level of user friendliness. The importance of performance indicates that designers and implementers can now concentrate on functionality of the software in the enterprise context. The ever growing IT-savviness of employees and their familiarity with social media tools on the Internet make it possible to push performance by adding new functions without overburdening users.

5.5 Conclusion

To answer the questions defined in the introduction, this work develops a model of ESM adoption based on UTAUT but differentiating between content contribution and content consumption as two modes of ESM use. We obtained mixed results: On the one hand the model provides a good explanatory power for content contribution but on the other hand it explains a relatively low percentage of the variance in content consumption. While contribution is significantly and positively affected by performance expectancy, social influence and facilitating conditions, the impact of social influence on consumption is negative. This results offer not only insights into the drivers of the different types of ESM adoption but also reveal that splitting the dependent variable is necessary for technologies with heterogeneous uses. Notably, the findings of this work show that although a pure content consumption is primarily driven by the wish for performance improvements (similar to content contribution), the social environment does not support this behavior (in contrast to contribution).

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Appendix

A. Items

Intention to contribute content (CONT):

CONT1: I intend to use blogs/wikis/social networks and publish content in the future.

CONT2: I predict I would use blogs/wikis/social networks and publish content in the future.

CONT3: I plan to use blogs/wikis/social networks and publish content in the future.

Intention to consume content (CONS):

CONS1: I intend to use blogs/wikis/social networks in the future, without publishing any content.

CONS2: I predict I would use blogs/wikis/social networks in the future, without publishing any content.

CONS3: I plan to use blogs/wikis/social networks in the future, without publishing any content.

Performance expectancy (PEEX):

PEEX1: I believe blogs/wikis/social networks will be useful for communication.

PEEX2: Using blogs/wikis/social networks will enable me to accomplish work tasks more quickly.

PEEX3: Using blogs/wikis/social networks will increase my productivity.

Effort expectancy (EFEX):

EFEX1: Using blogs/wikis/social networks will not require a lot of mental effort. (dropped)

EFEX2: I believe blogs/wikis/social networks will be easy to use.

EFEX3: Using blogs/wikis/social networks will be easy for me.

Social influence (SOIN):

SOIN1: People who influence my behavior think that I should use blogs/wikis/social networks.

SOIN2: People who are important to me think that I should use blogs/wikis/social networks.

SOIN3: The senior management of this business thinks I should use blogs/wikis/social networks.

Facilitating conditions (FACO):

FACO1: I have the resources necessary to use blogs/wikis/social networks.

FACO2: I have the knowledge necessary to use blogs/wikis/social networks.

FACO3: A specific person (or group) is available for assistance with difficulties with blogs/wikis/social networks.

Essay VII

Titel

A Reference Algorithm for Enterprise Search

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A Reference Algorithm for Enterprise Search

Abstract

Purpose

In enterprises, knowledge workers are confronted with the challenge of efficient information retrieval, which is one of the most important barriers to knowledge reuse. This problem has been intensified in recent years by several organizational developments such as an increase in data volume and the number of data sources.

Design/methodology/approach

Addressing the different requirements between enterprise and web search, we in this paper, develop a reference algorithm for enterprise search that integrates aspects from personalized, social, collaborative, and dynamic search. We investigate the performance of a typical instance of our algorithm through a laboratory experiment.

Findings

We find that this instance outperforms rather traditional approaches to enterprise search regarding several performance measures.

Research limitations/implications

The integration of personalized, social, collaborative, and dynamic search can improve information retrieval. We have investigated a reference algorithm through a laboratory experiment that can be seen as starting points for future research. Our experiment was conducted among students. Future research can evaluate it the environment of a real enterprise.

Practical implications

Because of the modular structure of our algorithm, it can easily be adapted by enterprises to their specificities by concretization. We discuss the components which can be configured during the adaption process.

Originality/value

Our algorithm combines different search approaches. It automatically accounts for varying vocabularies between querying users and the creators of documents as well as between different groups of users. It also provides logs that can be used for a group-specific query completion.

Keywords: Enterprise search Reference search algorithm Dynamic search Collaborative search Ant colony optimization

1. Introduction

The ability of an enterprise to integrate and reuse the sometimes highly specialized knowledge of its employees has been identified as a major chance for gaining competitive advantages (Grant, 1996). Therefore, many enterprises have established internal repositories to support the explication of this knowledge, its storage, its transfer, and, eventually, its reuse (Alavi and Leidner, 2001). However, only few employees utilize the knowledge stored in these repositories (Davenport et al., 2003; Desouza, 2003). In search for an explanation, difficulties in finding suitable documents efficiently have been identified as the major barrier to knowledge reuse (Davenport and Pruzak, 1998), leading to high search costs and opportunity costs for enterprises (Feldman and Sherman, 2004). Functionalities for information retrieval within an enterprise (enterprise search) have long been undeveloped and highly inefficient (Hawking, 2004). In addition, recent changes in the organizational environment such as the availability of more data and data sources (McAfee and Brynjolfsson, 2012), the greater number of employees working with data (Hänel and Schulz, 2014), and the democratization of information in the enterprise (Li et al., 2014) further emphasize the need for new enterprise search functionalities that can help to overcome this barrier. This can also be seen by the fact that three out of six constituting technology characteristics of Enterprise 2.0 (search, links, and tags) directly relate to enterprise search (McAfee, 2006).

Early search algorithms have mostly relied on a simple pattern matching between the search query and a document's content. Later, search engines have improved this approach by incorporating the link structure to rank the relevance of web content (Page et al., 1999). In the last years, four streams have emerged that each address one of the disadvantages of this approach: *personalized* and *social search* taking into account the querying user's personal characteristics and social relationships (resp.) to adjust the ranking of the results, *collaborative search* aiming to exploit the information provided by historic search sessions (by potentially other users), and *dynamic search* considering search sessions which consist of multiple search queries. However, most of the algorithms originating from these streams were designed especially for web search. Attempts have been made to transfer such algorithms to enterprise search, but it soon has been recognized that this is hard to accomplish (O'Leary, 1997) given the different nature of these domains (e.g., the strongly differing numbers of potential users and results, no organic link structure on the intranet, etc., (McAfee, 2006)). The few algorithms that have especially been designed for enterprise search (e.g., Ronen et al., 2009) have two important limitations:

First, while some of them combine more than one of the four search streams described above, the unique chance to do so in the domain of enterprise search is often overlooked. In the environment of an enterprise search engine (ESE), users can easily be identified by their account, so that their activities can be tracked and logged across various systems. This enables a special form of collaborative search: for a search session, it can be predicted using historical information on previous search sessions 1) whether it will be successful, 2) which document the querying user is likely to search for, and 3) how she will refine her search queries (integrating dynamic search). The available information can be weighted by the strength of her similarity and relationship with the previous querying users (integrating personalized and social search).

Second, many existing enterprise search algorithms were designed specifically for the enterprise in which they are deployed. They often are proprietary and, therefore, kept a secret. Even if their code is disclosed they still cannot simply be deployed in other enterprises if the latter exhibit different characteristics (e.g., use a different file structure). Thus, elaborate transfer processes are necessary to adapt the algorithm.

In this paper, we address both limitations by developing a reference algorithm for enterprise search that integrates facets of personalized, social, collaborative, and dynamic search. Our algorithm is based on a rather general and modular architecture that allows to control for each of these components separately. Enterprises can adapt our reference algorithm to their specificities easily by concretization. We discuss the choices that can be made during this adaption process and describe one sample instance of our algorithm. Furthermore, we evaluate this instance using data from a laboratory experiment. Our results indicate that our algorithm is better suited to rank search results compared to traditional ESEs.

The remainder of this paper is organized as follows: First, we briefly review the four major streams of search in section 2. Then, we present our reference enterprise search algorithm in section 3 and discuss how it can be adapted by enterprises in section 4. We evaluate the sample instance by an experiment in section 5 and summarize the benefits and limitations of our algorithm in section 6, where we also give an outlook for possible future research.

2. Background

Besides keyword-based search paradigms that are based on the premise that documents are more relevant if their content or their attributes match the search query to a higher degree, researchers and practitioners have looked for possibilities to improve search algorithms in both web and enterprises. This has led to four major streams that search has evolved into during the last years: personalized search, collaborative search, social search, and dynamic search. The premises derived from these trends should serve as a guideline to build a reference algorithm for enterprise search that combines these approaches.

2.1 Personalized search

The actual goal of any search is to find documents that are relevant to the querying user's current informational need, not to the search query (e.g., Chirita et al., 2004; Shapira and Zabar, 2011). Thus, search algorithms should be based on a relevance concept that incorporates subjective relevance instead of being based on an objective relevance concept (such as mere pattern matching) only. This can easily be seen by the fact that different users searching with the same search query (e.g., "revenue report") might have different informational needs (e.g., the revenue report for their country). Personalization is an approach to alleviate this issue by considering information available on the querying user assuming that this information provides valuable insights on the relevance of documents. In the given example, her physical location could be used to decide which revenue report is most relevant to her. As a consequence, users with similar characteristics can be expected to have similar informational needs.

2.2 Social search

A social search engine enriches the traditional keyword-based approach with information about the querying user's relationships with other users (the social graph) to personalize the search results (Shapira and Zabar, 2011). This approach is based on the assumption that users which are closely connected with each other tend to have similar informational needs. In contrast to personalized search, where the users' personal attributes are crucial to evaluate the similarity between users, social search measures this similarity based on the type and strength of connections within the users' social network (Watts et al., 2002). Note that in the context of enterprise search, personalized and social search are strongly linked because employees with similar characteristics (e.g., the same location) often are also socially connected (e.g., being colleagues).

2.3 Collaborative search

Search engines are used by more than one person. This soon led to the idea of collaboration, that is, the hypothesis that the querying user can benefit from the experience of users who have searched earlier. This can happen either explicitly or implicitly (Papagelis and Zaroliagis, 2007).

Users can explicitly annotate documents they have found (e.g., with ratings, comments, or tags, (Bao et al., 2007)). This information can then be incorporated into a search algorithm to re-rank the results in accordance with other users' explicit feedback (Shapira and Zabar, 2011). The assumption behind this idea is that documents with good ratings are more relevant to the querying user than poorly rated documents because good ratings indicate a high quality.

Implicit collaboration takes place when search histories and logs of other users are utilized to identify similar search patterns among similar users. A search algorithm that takes implicit collaboration into account assumes that users searching with the same search query often have the same informational need. At its simplest, each document's relevance estimate can be adjusted by the number of searches starting with the querying user's search query and ending with the document.

2.4 Dynamic search

Early search algorithms have assumed the search process of a user to be static, that is, starting with a user entering a search query and ending with her selecting one of the documents returned by the algorithm in response to this query. In the last decade, it has been recognized that search processes are rather dynamic with users refining their initial search query until they are satisfied with the ranking of the results (Rieh, 2006). In particular, prior research has argued that users start with a rather short search query consisting of only a few keywords and extend it step by step if necessary (Aula et al., 2010). The assumption behind the combination of collaborative and dynamic search is that users prefer search paths that have already been used by other users.

3. Reference algorithm

We next present a reference enterprise search algorithm that enterprises can adapt to their individual specificities (e.g., their organizational structure) by concretization. An exemplary instance is given and evaluated using data from a laboratory experiment in section 4.

3.1 General approach

We begin with some general considerations. Each time a user u with an informational need in (e.g., the revenue for Germany in 2014) enters a search query q (e.g., "revenue") into an ESE, the goal of its underlying algorithm is to rank all available documents by their estimated relevance (and possibly to discard documents with an estimated relevance below some critical value). "Relevance" here often is interpreted as "relevance to q"; however, one should more precisely speak of "relevance to the ESE's estimate $\widehat{in}$ of in". While $\widehat{in}$ is usually based on q, additional factors may be included in its calculation. In particular, personalized search, that is the incorporation of data describing u, has been found to improve the precision of $\widehat{in}$ (e.g., Qiu and Cho, 2006).

The precision of $\widehat{in}$ is also affected by its specificity, which in turn is largely determined by the specificity of q. This implies a trade-off: If q is chosen too unspecific, $\widehat{in}$ is less specific than in. Thus, documents that are not relevant to in may falsely be considered relevant and, therefore, rank high. If q is chosen too specific, on the other hand, $\widehat{in}$ is more specific than in. Documents being relevant to in may falsely be considered not relevant and rank low or even get discarded. Furthermore, the number of words u has to enter (and hence, her work) tends to increase with the specificity of q. Users for these reasons usually employ several queries during one search session. More precisely, they often begin a session with a rather unspecific query q_0, which they then refine in several rounds $t = 1,2,\ldots$ to more specific queries q_t (Aula et al., 2010). This process continues until they either find a document fulfilling in through the ranking displayed by the ESE or decide to cancel the session.

The state s_t of a user's session in round t is completely determined by the query history $\mathbf{q}_t = (q_0, \ldots, q_t)$ up to this round. However, it is often reasonable to use a *query history transformation function* state to map $\mathbf{q}_t$ to s_t; that is, to set $s_t = \mathrm{state}(\mathbf{q}_t)$. While state can always simply be chosen as $\mathrm{state}(\mathbf{q}_t) = \mathbf{q}_t$, enterprises should benefit from choosing a more elaborated transformation function on the basis of their individual characteristics. We will discuss this choice later on. After the last query refinement round T, the final state s_{T+1} of the session can be indicated by the resulting document if it ended successfully and by a special state for cancelled searches otherwise.

A single finished session can be visualized as a graph containing its states as nodes and its state transitions as edges (fig-session). Different node types can be used to distinguish the states s_t for $t = 0, \ldots, T$ (query nodes, drawn elliptical) from s_{T+1} (either a document node, drawn rectangular, or the cancel node, drawn rhombic). By construction, query nodes always have at least one outgoing edge, while document nodes and the cancel node can only have ingoing edges.

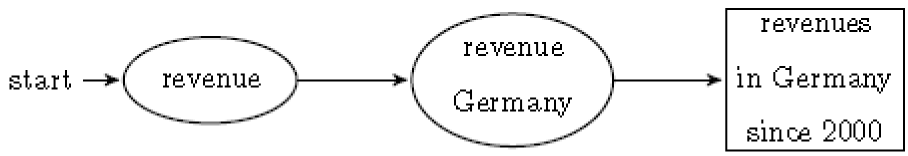

Figure 1: Graph visualizing a single search session

The behavior of u (which queries she employs during one session, which document she finally opens, and when she decides to cancel the search) depends on in. E.g., if u begins the search session with the query "revenue", she is more likely to refine this query to "revenue Germany" than to "revenue France" if her informational need is the revenue for Germany. Formally, this corresponds to the probability $\mathrm{P}_u(x \rightarrow y)$ for a transition from a state x to a state y of u's search session depending on in; that is, $\mathrm{P}_u(x \rightarrow y|in) \neq \mathrm{P}_u(x \rightarrow y)$. As can easily be shown using Bayes' theorem, a direct consequence of this assumption is $\mathrm{P}(in|x \rightarrow y) \neq \mathrm{P}(in)$; that is, the knowledge about u using the edge from x to y changes the probability distribution $\mathrm{P}(in)$ of in. This, in turn, leads to the fact that the queries u has employed up to round t of her search session provide information on in. However, by construction, this information is completely contained in $\mathbf{q}_t$ and, thus, for appropriate query history transformation functions state, also in the current state s_t (Markov property).

$\mathrm{P}(in)$ can differ between users; that is, $\mathrm{P}(in)$ has to be replaced by a user-specific probability distribution $\mathrm{P}_u(in)$. E.g., an employee of a German subsidiary is usually more likely to search for the revenue for Germany than for the revenue for France. This example demonstrates that it often makes sense to let $\mathrm{P}(in)$ differ only between groups of users than between all users. Our algorithm is valid for both approaches (since we allow for defining groups that consist of a single user). It is determined by her characteristics $\mathbf{x}_u$ (e.g., her position in the organizational hierarchy and her country) through a *group assignment function* group ($g_u = \mathrm{group}(\mathbf{x}_u)$) to which group g_u a user u belongs. Our reference algorithm becomes personalized by incorporating $\mathbf{x}_u$ this way. For the integration of social search, we define a *group proximity function* prox that reflects the social proximity between u and the members of other groups. E.g., the proximity of the manager of a German subsidiary with the group of her employees may be higher than with the group of employees of a French subsidiary. For our reference algorithm, prox assigns to the combination of $\mathbf{x}_u$ and a group g a propensity score from the interval $[0;1]$ with $\mathrm{prox}(\mathbf{x}_u, g) = 1$ if and only if $g = \mathrm{group}(\mathbf{x}_u) = g_u$. We discuss appropriate choices of group and prox later on.

An important consequence of the behavior of u depending on in and the probability distribution of in depending on u's group proximities is that the latter can be used to forecast u's behavior. E.g., when u has searched for "revenue" and belongs to a group of employees of a German subsidiary, she is more likely to search for "revenue Germany" next than for "revenue France". Thus, the ESE should rank documents higher that relate to "revenue Germany" when u has searched for "revenue". This is the essential idea on which our reference algorithm is based. Formally, we define:

$$\mathrm{P}_u(x \Rightarrow y) = \begin{cases} 1, \text{ if } y = x \\ \mathrm{x} \sum_z \mathrm{P}_u(x \rightarrow z) \cdot \mathrm{P}_u(z \Rightarrow y), otherwise \end{cases} \tag{1}$$

with z indexing all states that can be reached from x in one step. $\mathrm{P}_u(x \Rightarrow y)$ is the probability that a search session that is in a state x will eventually reach a state y (after any number of further rounds). $\mathrm{P}_u(x \Rightarrow y)$ accounts for the fact that some potential states (e.g., the document nodes and the cancel node) can be reached via several ways. In the given example, u may refine her initial query to "revenue 2014" instead of "revenue Germany". Nevertheless, she may eventually reach the same document (e.g., "revenues in Germany since 2000"), so that both ways have to be considered to calculate the relevance of this document when u has entered "revenue". Note that $\mathrm{P}_u(x \Rightarrow y) = 0$ for all y if x is a document node or the cancel node because these nodes end the search session. Besides that, we set $\mathrm{P}_u(x \Rightarrow x) = 1$ because in state x, state x already has been reached. Now our central assumption can be stated as

$$\pi(\widehat{in}_t) = (\mathrm{P}_u(s_t \Rightarrow y), y \in \mathrm{TC}(s_t))' \tag{2}$$

with $\mathrm{TC}(s_t)$ characterizing the transitive closure of s_t (that is, all states that can be reached from s_t). (2) means that the vector of the probabilities with which a search session of a user u will reach the accessible states given its current state s_t reflects an estimate $\widehat{in}_t$ of u's informational need in through a representation π. In other words, this vector provides information on how much each state that is accessible from s_t fits in. $\pi(\widehat{in}_t)$ can be used to calculate the relevancies of the available documents to in and hence, to rank them.

Our definition of the total relevance $\mathcal{TR}_d$ of a document d contains three factors that we discuss next. First, we consider its subjective relevance $\mathcal{SR}_d$, which we operationalize as

$$\mathcal{SR}_d = \frac{1}{\lambda} \cdot \pi(\widehat{in}_t) * (\mathrm{P}_u(y \Rightarrow d), y \in \mathrm{TC}(s_t)), \tag{3}$$

where $*$ symbolizes the scalar product and $\lambda = \pi(\widehat{in}_t) * \mathbf{1}$ is a normalization constant. $\mathcal{SR}_d$ combines the information on how much each state y fits in with the information on how probable it is that u will eventually open d given that her search session has reached y. Since the latter is subjective to (the group proximities of) u, we secondly take into account d's objective relevance $\mathcal{OR}_d$. For this purpose, we define a function $\mathrm{match}(y, d)$ as $\mathrm{match}(y, d) = \mathrm{query\_match}(y, d)$ if y is a query state, $\mathrm{match}(y, d) = \mathrm{doc\_match}(y, d)$ if y is a document state, and $\mathrm{match}(y, d) = 0$ if y is the cancel state. query_match and doc_match are *query and document matching functions* that express the degree of match between y and d for query and document states y (resp.) through a value from the interval $[0; 1]$. $\mathcal{OR}_d$ is then operationalized similarly to $\mathcal{SR}_d$ as

$$\mathcal{OR}_d = \frac{1}{\lambda} \cdot \pi(\widehat{in}_t) * (\mathrm{match}(y, d), y \in \mathrm{TC}(s_t)). \tag{4}$$

It combines the information on how much each state y fits in with the degree of match between y and d. The third component we utilize is the quality $\mathcal{Q}_d$ of d that is determined on a scale from 0 to 1 through a *quality evaluation function* qual by d's characteristics $\mathbf{z}_d$; that is, $\mathcal{Q}_d = \mathrm{qual}(\mathbf{z}_d)$. Since $\mathbf{z}_d$ can include characteristics attributed to d by other users (e.g., a star rating), its incorporation represents a form of explicit collaborative search. Finally, a vector $\mathcal{TR}$ is calculated from the vectors $\mathcal{SR} = (\mathcal{SR}_d, d)'$, $\mathcal{OR} = (\mathcal{OR}_d, d)'$, and $\mathcal{Q} = (\mathcal{Q}_d, d)'$ through a vector-valued *scoring function* score. The total relevance $\mathcal{TR}_d$ of d is then given by the d-th row of this vector. By this approach, we allow for $\mathcal{TR}_d$ depending on the total relevancies of all other documents. The choice of query_match, doc_match, qual, and score will be discussed later on.

3.2 Ant Algorithm

So far, our reference algorithm is purely conceptual since in practice, $\pi(\widehat{in}_t)$ cannot be determined. This is because the probabilities $\mathrm{P}_u(x \Rightarrow y)$ are based on the transition probabilities $\mathrm{P}_u(x \rightarrow y)$, which are not known. As mentioned earlier, the latter characterize the user u's behavior, that is, what she will do in the next round when the search session is in state x. We now integrate implicit collaborative search as the final component of our algorithm, which means that we assume that $\mathrm{P}_u(x \to y)$ can be estimated on the basis of previous search sessions that also have been in state x. This is moderated by the group of u and u's proximities to other groups. E.g., if a high proportion of users from the same group as u who had searched for "revenue" have searched for "revenue Germany" next, it is likely that u also will refine her search query in this way.

A straightforward approach to express this idea in a formula would be to estimate $\mathrm{P}_u(x \to y)$ by (a weighted average of) the relative frequencies of the usage of edge $x \to y$ from state x by all user groups. We employ Ant Colony Optimization (ACO, Dorigo et al., 1996) as a more general approach that was recently introduced in dynamic search (Albakour et al., 2011) and includes ACO as a special case. In the terminology of ACO, a search session a corresponds to an ant travelling to a food source (a document fulfilling the searching user's informational need). On its way it drops a certain amount of pheromones on each way (edge) it passes. For the edge $x \to y$, this amount $\Delta\tau^a_{x \to y}$ is given by

$$\Delta\tau^a_{x \to y} = \begin{cases} \frac{Q}{C^a}, \ if\ \exists t\colon s^a_t = x \wedge s^a_{t+1} = y \\ 0, \ otherwise \end{cases} \tag{5}$$

where s^a_t marks the states of a for all its rounds t, Q is a constant, and C^a is the "cost" of a's complete way. After a defined period W (e.g., a day or 100 ants), the total amount $\tau^g_{x \to y}$ of pheromones on $x \to y$ from a user group g (with $\tau^g_{x \to y}$ initially being 0 for each g) is updated as

$$\tau^g_{x \to y} \leftarrow (1 - \rho^g) \cdot \tau^g_{x \to y} + \sum_{a | g_{u^a} = g} \Delta\tau^a_{x \to y} \tag{6}$$

where u^a is the user who has instanced a. $\rho^g \in [0; 1]$ are group-specific evaporation coefficients that specify the percentage of $\tau^g_{x \to y}$ that evaporates within the duration of W. The choice of Q, C^a, W, and ρ^g will be discussed later on.

A set of finished search sessions can be visualized by combining their individual graphs. The nodes and edges of the resulting graph (fig-sessions) represent the states and state transitions that have occurred in at least one session (resp.). On each edge $x \to y$, the amount of pheromones $\tau^g_{x \to y}$ can be drawn for each group. In the given example, two different groups exist (indicated by white and black pheromones) that obviously have different informational need distributions: While group 1 (white) seems to be mainly interested in the revenue for Germany and Europe, for which two matching documents exist, group 2 (black) seems rather to search for the revenues in the USA, for which no document exists (leading to a high rate of cancelled searches). As will become clearer later, the amount of pheromones dropped by each ant can be smaller than 1, what is symbolized in the figure by half circles.

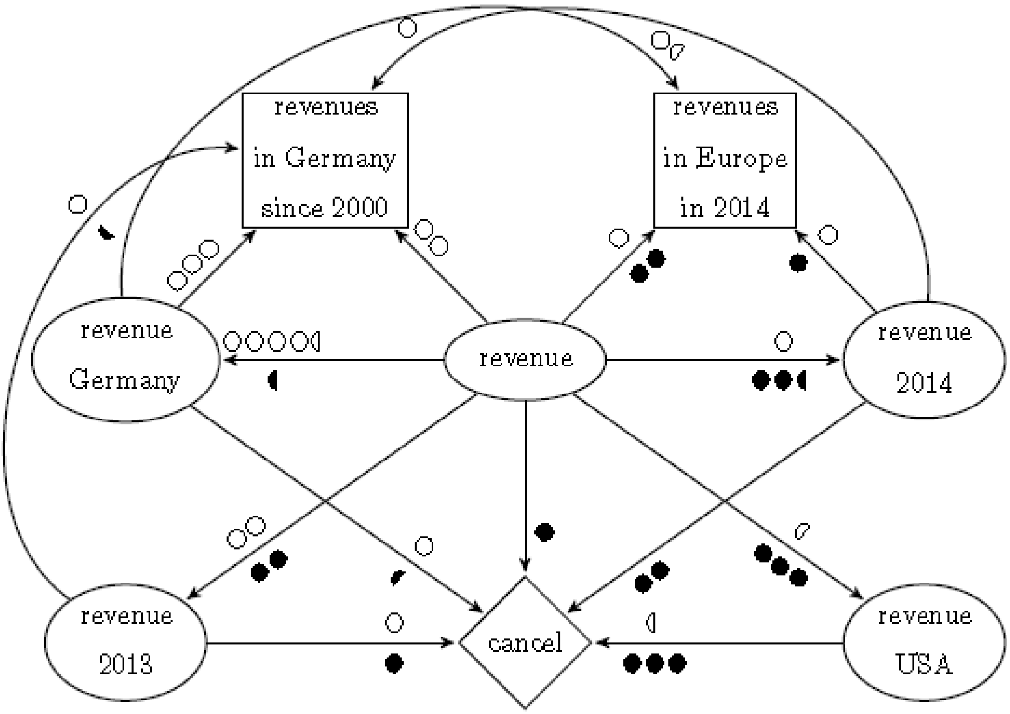

Figure 2: Graph visualizing a set of search sessions with pheromones of two user groups

Now the transition probability $\mathrm{P}_u(x \to y)$ can be estimated by the total amount of the pheromones dropped at $x \to y$ relative to the total amount of pheromones dropped on all outgoing edges $x \to z$ of x, both weighted by the group proximity function prox:

$$\widehat{\mathrm{P}}_u(x \to y) = \frac{\sum_g \mathrm{prox}(u,g) \cdot \tau^g_{x \to y}}{\sum_g \mathrm{prox}(u,g) \cdot \sum_z \tau^g_{x \to z}} \tag{7}$$

Replacing the probabilities $\mathrm{P}_u(x \to y)$ with their estimates $\widehat{\mathrm{P}}_u(x \to y)$ in (1), one gets estimates $\widehat{\mathrm{P}}_u(x \Rightarrow y)$ of $\mathrm{P}_u(x \Rightarrow y)$, from which an estimate $\hat{\pi}(\hat{in}_t)$ of $\pi(\hat{in}_t)$ can be derived. $\hat{\pi}(\hat{in}_t)$ in turn can be used to get estimates of the subjective and objective relevance of each document, which in combination with the documents' qualities lead eventually to estimates $\widehat{\mathcal{TR}}_d$ of their total relevancies $\mathcal{TR}_d$. Finally, the ranking of documents presented by the ESE is given by sorting them according to $\widehat{\mathcal{TR}}_d$ in descending order.

4. Adaption

We now outline how enterprises can adapt our reference algorithm in dependence on their individual characteristics.

4.1 The query history transformation function

Enterprises have to choose a query history transformation function state that converts the searching user's query history $\mathbf{q}_t = (q_0, \ldots, q_t)$ in round t to a state s_t of her search session; $s_t = \mathrm{state}(\mathbf{q}_t)$. This choice is very important since the number of states generated, the interweaving of different search sessions, and the compliance of search sessions with the Markov property depend on state. These factors entail a trade-off between 1) how fast the algorithm learns and 2) how precise its results are. We illustrate this by some examples.

As mentioned earlier, the simplest option is to choose $\mathrm{state}(\mathbf{q}_t) = \mathbf{q}_t$. This function always complies with the Markov property since s_t contains the whole information of $\mathbf{q}_t$ by construction when it is employed. Using this function, one does not need to care manually about whether, e.g., the order of queries contained in $\mathbf{q}_t$ makes a difference. This is because state would assign different states to differently ordered query histories, so that the algorithm would account for potential differences automatically. However, this desirable property comes at a high price: by assigning two query histories to the same state only if they are exactly identical, the number of states created in total becomes extremely high. This results not only in a computationally intensive calculation of $\pi(\widehat{in_t})$ but also in a very loose interweaving of different search sessions. E.g., if the initial queries of two sessions are "revenue Germany" and "Germany revenue", these sessions would not share any state despite their obvious similarity. The amount of pheromones deposited on each edge is thus usually very low, so that the algorithm may learn only very slowly and the variance of the estimator $\widehat{\mathrm{P}}_u(x \to y)$ may be rather high.

For almost all other transformation functions, the Markov property is not fulfilled by construction but rather imposes an assumption. The consequences can be illustrated by the extreme choice of $\text{state}(\mathbf{q}_t) = q_t$ (that is, ignoring all queries except the current one). This function is valid in an environment where users cumulate keywords (e.g., search for "revenue" first, "revenue 2014" second, and "revenue 2014 Germany" third) since the last query in this case contains the information of the former queries. Otherwise (e.g., if they search for "revenue" first and "Germany" second), the information that s_t provides may not suffice to estimate the user's informational need correctly. $\widehat{in}_t$ and, hence, the ranking of documents may, therefore, be biased.

A multi-purpose transformation function that we suggest for most ESEs is

$$\text{state}(\mathbf{q}_t) = \cup_{r=1}^{t} kw(q_r), \tag{8}$$

where $kw(q_r)$ denotes the set of keywords contained in q_r. E.g., for two queries $q_0 =$ "revenue" and $q_1 =$ "revenue2014", $\text{state}(\mathbf{q}_1) = \{\text{"revenue"}, \text{"2014"}\}$. (8) has three properties: first, it ignores the order of queries within a query history and the order of keywords within a query. This reduces the number of potential states by a number much greater than the faculty $t!$ of t. Second, it regards keywords entered redundantly (as "revenue" in the given example) as if entered only once. Third, it automatically cumulates keywords so that the Markov property is fulfilled by construction if the assumption holds that the order and frequency of queries and keywords does not make a difference. As a consequence of these properties, similar search sessions easily can get interweaved so that the algorithm learns fast and $\widehat{\mathrm{P}}_u(x \to y)$ has a low variance. Note that (8) could still be improved by incorporating a dictionary for synonyms, misspellings, etc.

4.2 The group functions

Ideally, enterprises should choose the group assignment function group and the group proximity function prox in a way that exactly all users u within a group have the same probability distribution $P_u(in)$ of their informational need and that prox reflects the similarity of these distributions between groups. In practice, however, this can be hardly accomplished since these distributions are unknown. Therefore, care has to be taken when choosing group and prox: on the one hand, too few groups can bias $\widehat{in}_t$ towards an average informational need. The extreme case of a single group would be a direct contradiction to our assumption of $P_u(in)$ differing between users. If the number of groups is chosen too high, on the other hand, differences between these distributions are assumed that do not exist, what leads to a loss of efficiency. Furthermore, the number of search sessions of users belonging to a certain group and, therefore, the amount of pheromones deposited by this group would be rather low. This again leads to a high variance of $\widehat{\mathrm{P}}_u(x \rightarrow y)$. A higher (lower) number of users corresponds to a higher (lower) number of informational need distributions and should, therefore, be met by a higher (lower) number of groups.

We propose the following three-step procedure for choosing group and prox: First, all variables $x_1, \dots, x_K$ that can be assumed to have an influence on $\mathrm{P}_u(in)$ (e.g., organizational position, country, etc.) are selected from the intersection of all user characteristics $\mathbf{x}_u$. Second, variables having a continuous domain or taking too many different values for the given set of users (e.g., a user's age) are replaced with clustered versions. Third, group and prox are defined as

$$\mathrm{group}(\mathbf{x}_u) = (x_{1_u}, \dots, x_{K_u}) \text{ and} \tag{9a}$$

$$\mathrm{prox}(u, g) = \frac{1}{K} \cdot \sum_{k=1}^{K} 1(x_{k_u} = x_{k_g}), \tag{9b}$$

where x_{k_u} and x_{k_g} represent the values of x_k for u and each member of g (resp.) for $k = 1, \dots, K$ and $1(\cdot)$ symbolizes the indicator function. This procedure has two major advantages: first, it can be adjusted to most enterprises because its specificities can be easily taken into account by the selection of the variables $x_1, \dots, x_K$. Second, it does not require an explicit decision on the number of groups being created since this number results as an implicit consequence of the decision on $x_1, \dots, x_K$.

4.3 Further functions

The matching functions query_match and doc_match measure the degree of match between a query state or a document state y and a document d (resp.). For this purpose, the content of a document is often summarized by so-called tags, which have been either assigned to the document by users manually or generated from the document's content automatically (e.g., Chirita et al., 2007). Assuming that all documents are characterized by a set of tags $tags(\cdot)$, query_match and doc_match can be defined as

$$\mathrm{query\_match}(y, d) = \mathrm{sim}(kw(y), tags(d)) \text{ and} \tag{10a}$$

$$\mathrm{doc\_match}(y, d) = \mathrm{sim}(tags(y), tags(d)). \tag{10b}$$

As a simple similarity measure sim, the Jaccard index

$$\mathrm{sim}(A, B) = \frac{|A \cap B|}{|A \cup B|} \tag{10c}$$

for two sets A and B can be used. More elaborate similarity measures can take into account linguistic subtleties.

The quality evaluation function qual which estimates a document d's quality q_d by its characteristics $\mathbf{z}_d$ does largely depend on the nature of $\mathbf{z}_d$. E.g., if $\mathbf{z}_d$ contains a single value z_d expressing the perceived quality of d by a star rating on a scale from z_{min} to

z_{max}, qual can simply be defined as

$$\text{qual}(\mathbf{z}_d) = \frac{z_d - z_{min}}{z_{max} - z_{min}}. \tag{11}$$

qual may also be based on other variables expressing further explicit collaborative behavior, such as user comments, recommendations, etc.

The goal of the scoring function score is to weigh the subjective relevancies $\mathcal{SR}$ against the objective relevancies $\mathcal{OR}$ and to adjust the result by the documents' qualities $\mathcal{Q}$. For this purpose, we suggest a two-step procedure: in the first step, a vector $\mathcal{R}$ is calculated as a weighted average of $\mathcal{SR}$ and $\mathcal{OR}$:

$$\mathcal{R} = \alpha \cdot \mathcal{SR} + (1 - \alpha) \cdot \mathcal{OR}. \tag{12a}$$

The weight $\alpha \in [0; 1]$ may differ between periods: in the beginning, when the total amount of pheromones is low and the algorithm has not learned much, it seems reasonable to use a low value for α (that is, to prefer $\mathcal{OR}$ over $\mathcal{SR}$). This value can be increased when the estimates $\widehat{\mathrm{P}}_u(x \Rightarrow y)$ become more precise over time. In the second step, score is defined as

$$\mathcal{TR} = \text{score}(\mathcal{R}, \mathcal{Q}) = \mathcal{R} + \text{lex} \tag{12b}$$

with lex representing a vector-valued function that achieves a lexicographical ordering of documents by $\mathcal{R}$ first, query_match second, and by $\mathcal{Q}$ third (e.g., by adding values based on query_match and $\mathcal{Q}$ that are small enough to retain the principal order of $\mathcal{R}$).

4.4 ACO parameters

If Q in (5) is chosen as a constant not only over all ants (search sessions) but also over all periods, its value does not matter and can be normalized to 1. However, it may make sense to alter Q between time periods to adjust the learning process of the algorithm to seasonality. An extreme example is setting Q to 0 for a certain period, which results in the algorithm learning nothing in this period. Another example is setting Q in each period to the average pheromone level over all used edges of the previous period (Albakour et al., 2011), what basically corresponds to attributing higher importance to periods with more search sessions in the previous period.

When choosing a period duration W, enterprises face a trade-off: on the one hand, the algorithm should learn as fast as possible. This advocates for frequent updates, that is, a short period duration. In the extreme case, an update could take place after every search session. However, this approach is suited only for enterprises with a low number of search sessions per time unit. This is because, on the other hand, updates of the total amount $\tau^g_{x \to y}$ of pheromones on an edge $x \to y$ for a group g implicate the necessity of updating also $\widehat{\mathrm{P}}_u(x \to y)$ and $\widehat{\mathrm{P}}_u(x \Rightarrow y)$ for all users u. This is computationally costly and prevents these values from being stored for a longer time. Thus, a period should ideally end as soon as the benefit from the algorithm learning from the incurred search sessions outweighs the additional computational costs.

For the cost C^a of ant a's way, two choices are reasonable. First, C^a can be set to a constant normalized to 1 for all ants. The pheromones dropped in total on an edge $x \to y$ in this case correspond to the number of ants travelling from x to y, which leads to (7) being equivalent to the usage of relative frequency mentioned earlier. This approach would be suited for ESEs with users who do not change their searching behavior over time. However, prior research has shown that the latter usually is influenced by the user's experience (Hölscher and Strube, 2000) and visual aids the ESE provides, such as query completion. The second approach accounts for this by setting $C^a = T^a + 1$, where T^a denotes the number of query refinements in session a. That is, ants drop less pheromones on an edge $x \rightarrow y$ if their total way is longer. Thus, longer ways requiring more query refinements to the final state become less important in the long run. This corresponds to experienced users avoiding such ways.

The pheromone evaporation coefficients ρ^g determine how fast the algorithm forgets what it has learned from the behavior of users belonging to a group g. Ideally, they should be chosen in a way that they reflect how fast 1) the distribution of informational needs of the members of g and 2) documents relating to their informational needs change (e.g., how often new documents are added). If 1) and 2) change only slowly, ρ^g may be set to 0. This choice has yielded the best results in prior research analyzing a university search engine (Albakour et al., 2011), for which at least the informational needs (e.g., lecture material) can be expected to vary only slightly over time. For $\rho^g = 1$, no learning would take place since the algorithm would immediately forget what it has learned. Thus, even for enterprises and groups for which 1) and 2) change fast, moderate values for ρ^g should be chosen.

5. Evaluation

In this section we evaluate an instance of our reference algorithm through an experiment. First, we describe the design of this experiment, the dataset we have obtained, and the instance of our reference algorithm that we have tested. We then explain how we have measured the algorithm's performance and present and discuss its results.

5.1 Experimental setup and dataset

We conducted a laboratory experiment with 146 students (76 undergraduate, 70 graduate; 60 female, 86 male). Such a setup is more controllable than a field study in a real enterprise, what leads to a higher internal validity (Straub et al., 2004). Particularly, the participants are unbiased by experience made with specific enterprise search functions.

Every participant had to complete 10 search tasks from an enterprise context, leading to $146 \times 10 = 1{,}460$ search sessions in total. In 28 cases students did not answer a search tasks, so that $1{,}432$ search sessions remain. The search tasks differed in both, difficulty and specificity. More precisely, the first 5 tasks were specific to two characteristics, 1) the location and 2) the department of a fictitious employee identity randomly assigned to each student (e.g., *In the next five years, what are the biggest risks in the sales department in Saxony?*), while the remaining tasks were more general in regard to these characteristics (e.g., *Can the company you work for be expected to downsize soon?*). On the basis of 1) and 2), the grouping functions group and prox were defined as in (9a) and (9b), with two possible values each. As a result, the students were assigned to one of $2 \times 2 = 4$ groups (40, 36, 36, and 34 members), with similarities of 0, 0.5, 0.5, and 1.

We proceeded as follows to create the set of documents: 32 other students (6 undergraduate, 26 graduate; 18 female, 14 male) were given the same search tasks before the actual experiment was carried out. For each task, they were asked to attribute tags to documents which contain the desired information (possibly among other things). Tags that were mentioned by at least 10% of the participants were used to create one target document for each search task. Thereby, we simulate that in the enterprise, documents are often tagged rather by standard users than by experts. Besides these 4×5 group-specific and 5 generic target documents, we created 975 additional "noise" documents that were tagged randomly using the set of tags assigned by the students and a set of added tags (e.g., other regions and departments). This resulted in 7.5806 tags per document on average. For all $1{,}000$ documents, a rating was randomly drawn from a discrete uniform distribution on $\{1; \dots; 5\}$, from which the document's quality was calculated by the quality function qual given in (11). No documents were added or removed during our experiment. Therefore, we set the pheromone evaporation coefficients p^g to 0 for each group as explained in sec-params.

The search process was carried out as follows: First, the participants were asked to enter a search query into a Google-like search mask. They were given the possibility to adapt this search query up to two times under the premise that no document will be found when using their initial search query. Then, the search sessions of all users were sorted in random order to avoid potential sequential bias. For each search session, we proceeded as follows: First, the documents were ranked by our algorithm based on the user's initial search query. Further, the number of documents the user is willing to view at most in one round is drawn from a uniform distribution on $\{10; \dots; 30\}$, reflecting one to three pages with ten results each. After that, the user is assumed to view every document in the order defined by the ranking until the target document is found (so that the search session ends successfully) or the number of maximum views is reached. In the latter case, this process is repeated with the user's second and third search query (if applicable). If the target document is still not found after the last round, the user is assumed to cancel the search session so that it ends unsuccessfully.

The query history transformation function state we employed is based on (8). To improve learning, we considered stop words (e.g., "the", "and", etc.), punctuation marks (1,274 cases), differing grammatical forms (2,548 cases), and synonyms (909 cases). This reduced the total number of keywords from $14{,}027$ to $12{,}753$ and the number of distinctive keywords from 867 to 285. The same rules were applied for the tagging of documents (146, 250, and 114 cases, resp.) reducing the total and distinctive numbers of tags from $1{,}028$ to 914 and from 295 to 149 (resp.). The scoring function score was chosen as described in (12a) with equal weights of the subjective and the objective relevance component ($\alpha = 0.5$). The latter was calculated according to $\mathrm{query\_match}$ and $\mathrm{doc\_match}$ as given in (10a) and (10b) (resp.) with the similarity function sim of (10c). Furthermore, the cost C^a of a search session a was chosen as the number of its rounds, and the constant Q was normalized to 1. Finally, we decided to update the pheromone levels after each search session focusing on the speed of learning rather than computational efficiency.

5.2 Performance measures and results

Several performance measures can be considered to evaluate our algorithm. We are mainly interested in the effort of the searching user to find a document, which we operationalize by how often she has to refine her search query and by the number of documents she has to view until she finds a document fulfilling her informational need. Furthermore, accounting for the maximum number of documents a user is willing to view before she decides to cancel her search session, we also consider the percentage of successful search sessions. Since all of the former performance measures evaluate the algorithm's ranking only in the range up to the number of the user's maximum document views, a common approach to evaluate the complete ranking is the mean reciprocal rank (MRR, e.g., Albakour et al., 2011). In our case, MRR can be defined as

$$MRR = \frac{1}{n} \cdot \sum_{a=1}^{n} \left(\frac{1}{T^a+1} \cdot \sum_{t=0}^{T^a} \frac{1}{r_{a,t}} \right), \tag{17}$$

where $r_{a,t}$ is the rank of a (by construction always existing) document d fulfilling the querying user's informational need in one of the $n = 1{,}432$ search sessions (ants) a in response to its state in round t.

Figure 3 illustrates the performance of the tested reference algorithm instance in comparison to a traditional pattern matching algorithm as a benchmark. The latter was implemented by ranking the results according to query_match only. The graphic shows that our algorithm performs significantly better than the benchmark as measured by the MRR ($t = 28.8729$, $p < 0.001$). The difference becomes the more pronounced the more searches have been carried out, that is, the more the algorithm has learned. Consequently, both the average numbers of query refinements and document views decrease over time. After the last search, our algorithm has reduced them by 50.7010% ($t = -31.5766,\ p < 0.001$) and 48.3790% ($t = -26.3605,\ p < 0.001$) compared to the benchmark. Since the numbers of documents the users are willing to view at most were kept constant for our algorithm and the benchmark, the number of cancelled searches also decreases and more searches end successfully. In the end, the percentage of successful searches is 23.8129 points higher using our algorithm than when using the benchmark ($t = 28.8729,\ p < 0.001$).

Our algorithm performed better for the group-specific tasks 1 to 5 than for the generic tasks 6 to 10 regarding all performance measures expect the MRR (see tab-comparison). When restricting the evaluation to successful search sessions, however, the performance is better for generic search tasks than for group-specific search tasks for all performance measures (query refinements: 0.1802 vs. 0.2129, views: 8.7275 vs. 10.8211, MRR: 0.5089 vs. 0.3624). This may be because the number of prior search sessions (ant trails) that are exploited is higher for generic than for group-specific tasks. Given that they do not lead to a wrong document (unsuccessful search sessions), the performance should be improved.

Next, we have compared the tested algorithm instance to another instance for which the distinction between groups was deactivated by changing group to a constant function, so that all users effectively are assigned to the same group. This approach can be compared to previous ACO-based search algorithms (Albakour et al., 2011). The single-group instance performs significantly worse regarding all performance measures (MRR: $t = -11.0000$, $p < 0.001$). This is as expected and can be explained by the ranking being influenced by information which does not match the searching user's group.

We have also explored the robustness of our algorithm by altering its parameters. First, we deactivated the subjective relevance component by setting $\alpha = 0$. This worsened the algorithm's performance significantly across all performance measures (MRR: $t = 1.8549$, $p = 0.0319$). We also tried the opposite and deactivated the objective relevance component by setting $\alpha = 1$. This did not lead to any significant changes (MRR: $t = 0.3047$, $p = 0.7607$). Finally, we replaced the ACO's pheromones with relative frequencies by setting the costs C^a to 1 for all search sessions. This also did not lead to any significant changes (MRR: $t = -0.2767$, $p = 0.7820$). These results underline the necessity to make the exact specification of our algorithm's instance dependent on the environment.

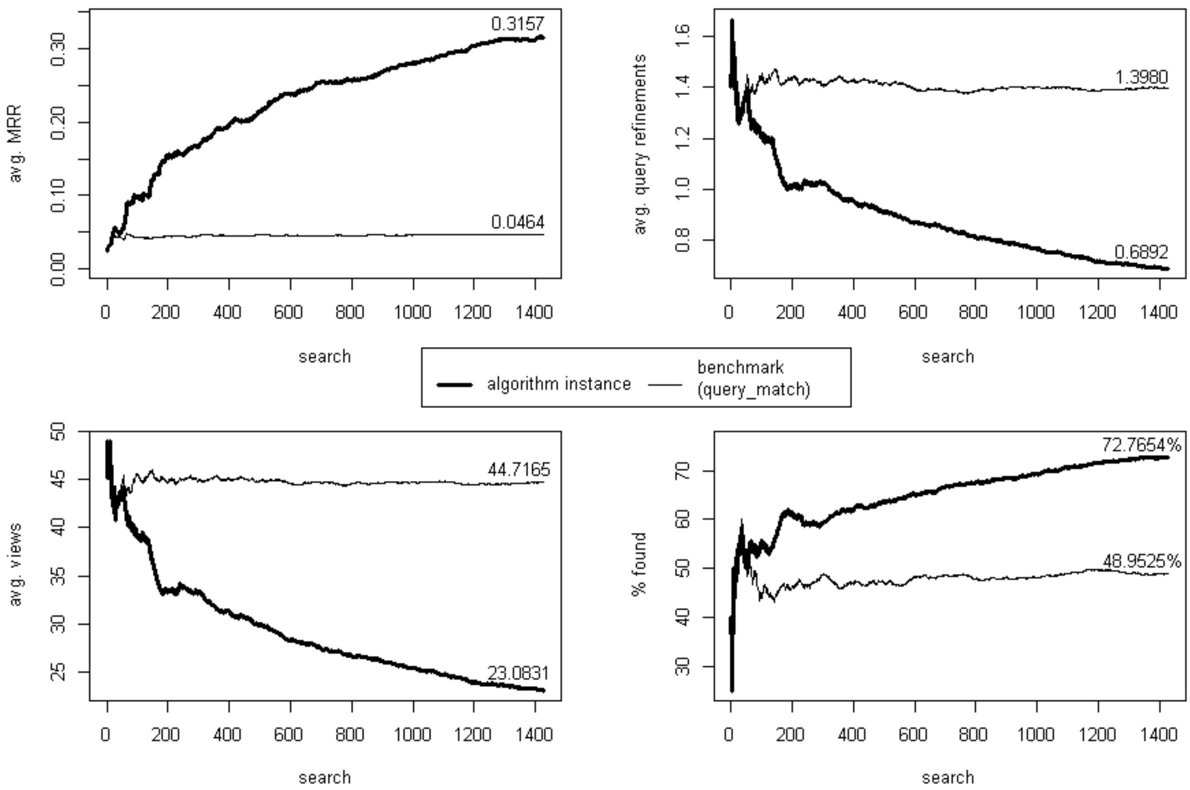

Figure 3: Algorithm performance

	avg. MRR	avg. query refinements	avg. views	% found
Main algorithm instance	0.3157	0.6892	23.0831	72.7654%
Group-specific tasks (1 to 5) only	0.2981	0.5531	19.4290	80.9655%
Generic tasks (6 to 10) only	0.3338	0.8289	26.8303	64.3564%
No distinction between groups	0.1854	1.0573	34.4253	49.0922%
Objective relevance only ($\alpha = 0$)	0.3079	0.7060	23.5440	71.9274%
Subjective relevance only ($\alpha = 1$)	0.3142	0.6760	22.7528	73.0447%
Relative frequencies ($C^a = 1$)	0.3167	0.6920	23.1103	72.7654%

Table 1: Comparison of dataset restrictions and algorithm variants

6. Discussion and Conclusion

The field of knowledge management in enterprises currently faces various challenges that can prevent knowledge workers from finding the information they are searching for. To overcome this barrier, we have presented a reference algorithm for enterprise search, which enterprises can adapt by tailoring it to their specificities. Our algorithm combines four current streams of search (personalized, social, collaborative, and dynamic), relying on information that is available in organizations since the advent of social knowledge management.

We now discuss some of the benefits of this integrated approach by some examples: first, our algorithm automatically accounts for different vocabularies between querying users and the creators of documents (and misspellings). To see this, consider a user searching with the keyword "Germany" in an environment where documents are tagged with "Deutschland" (the German word for "Germany") instead. This user may not find a suited document not until she reformulates her search query. This is learned by the algorithm, which in the long run will attribute a higher rank to this document when another user searches for "Deutschland" again (since the algorithm anticipates that she will search for "Germany" next). Second, our algorithms also accounts for different vocabularies between different groups of users (Cleverley, 2012) because it learns group-specifically. Third, it provides logs that could also be used for a group-specific query completion.

Investigating a reference algorithm through a laboratory experiment leads to some limitations that can be seen as starting points for future research. First, while we have evaluated a typical instance of our algorithm by an experiment with students, we have not evaluated its performance in a real environment of an enterprise. This is because the search logs typically collected by most existing ESEs do not suffice for an evaluation. Instead, our algorithm would first have to be implemented in a real environment before it can be evaluated with the data from the resulting log files. Second, we did not optimize our algorithm with respect to computational efficiency. While it can be argued that ESEs often run on high-performance servers, so that the absolute computational costs can be expected to be relatively low, (2) involves multiple recursive calculations and could, therefore, probably be improved regarding speed. Third, we have not explored the behavior of our algorithm for different settings (e.g., number of users, etc.), leaving space for future research.

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Essay VIII

Titel

Does One Model Fit All? – Exploring Factors Influencing the Use of Blogs, Social Networks, and Wikis in the Enterprise

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Does one model fit all? – Exploring factors influencing the use of blogs, social networks, and wikis in the enterprise

ABSTRACT

Although enterprise social media have become increasingly widespread, many intranet communities barely survive, miss their initially planned targets, or even get terminated. Although research on technology acceptance can be a useful approach to improve adoption rates, limited empirical research has been done to examine factors driving the adoption of enterprise social media (ESM). To address this gap, we develop a model of individual ESM adoption including technological and individual factors based on findings from collaboration and knowledge sharing research. Since different ESM tools such as blogs, social networks, and wikis can be employed for fundamentally different uses, we explain differences between individual adoptions of the three technologies by identifying their uses and gratifications from the perspective of employees. The model is tested in three parallel studies (one for each tool) among employees of an international technology company in the pre-implementation phase. We find substantial differences between the factors influencing the intention to adopt the three applications providing the basis to employ different ESM applications in a more effective way while considering organizational and employee needs.

KEYWORDS

Enterprise 2.0, enterprise social media, technology adoption, uses and gratifications, blog, social network, wiki

1. INTRODUCTION

Social media such as blogs, social networks, and wikis have become increasingly widespread in corporate intranets in recent years. Most of these applications have been previously used by millions of users in the private realm, which led companies to assume that employees will also embrace them at the workplace. While there are some reports of successful use of these applications in companies, many intranet communities barely survive or even get terminated. Market research firms and involved practitioners predict failure rates of up to 80% (Gartner 2013) and report very high dissatisfaction rates with ESM (Ward 2014). After the initial hype, enterprises start to raise questions for the reasons behind poor ESM adoption rates and consecutive missed business objectives. It has been suggested that an ad-hoc implementation of ESM without a strategy to get employees to interact and collaborate actively via the new technology is unable to fulfil the initially built expectations (McAfee 2009; Wattal, Racherla, and Mandviwalla 2010; Gartner 2013). A thorough understanding of the individual adoption process can help to identify factors fostering or preventing ESM use and, thereby, to improve implementation strategies.

A variety of models such as the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT) have been deployed to explain individual technology adoption in the information systems (IS) context (Davis, Bagozzi, and Warshaw 1989; Venkatesh et al. 2003). However, research indicates that general models of IS adoption can only provide limited insights into factors specific to a given technology (Venkatesh and Davis 2000). Therefore, focusing on certain IS can help to improve the explanatory power and resolve limitations regarding the level of detail (Venkatesh and Bala 2008). To meet this need, empirical examinations have been made for blogs (e.g., Chai, Das, and Rao 2011; Hsu and Lin 2008), social networks (e.g., Lin and Lu 2011; Steinfield, Ellison, and Lampe 2008), and wikis (e.g., Kuznetsov 2006; Yang and Lai 2010) used on the Internet. Although different uses and benefits can be expected for ESM (Richter, Riemer, and vom Brocke 2011), extant research on ESM is largely based on anecdotes and case studies (e.g., McAfee 2009; C. P.-Y. Chin, Evans, and Choo 2015) with very few exceptions. For example, Wattal et al. (2010) examine the influence of network externalities on the usage of intra-organizational blogs. Schöndienst et al. (2011)

deploy a slightly altered version of UTAUT to explore the drivers of micro-blogging usage in enterprises. Hester (2011) bases her study of enterprise wikis on the innovation diffusion theory to compare wiki-based and non-wiki based knowledge management systems. Despite these efforts to shed some light on individual adoption of specific ESM, an examination which compares the drivers of blogs, social network, and wiki adoption and explains similarities and differences is still missing.

Therefore, the objective of this study is to develop a model capturing factors affecting individual ESM adoption and consider the influences of expected uses and gratifications on employees' decisions to use a software. We address the following research questions in particular: (1) which technological and individual characteristics influence the individual intention to participate in blogs, social networks, and wikis? (2) How do different uses and gratifications of ESM applications lead to different effects of the identified antecedents on the intention to participate in ESM?

The paper is organized as follows: in the following section, we briefly define blogs, social networks, and wikis and identify different uses and gratifications that employees expect from their use based on our reasoning and prior research. Then, we develop the hypotheses to formulate the research model. Thereafter, we describe our study design and present study results for the three ESM types. Finally, the paper concludes with a discussion of its contributions and implications for practice.

2. ENTERPRISE SOCIAL MEDIA

2.1 Social Media vs. Enterprise Social Media

The term social media describes "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0 and that allow the creation and exchange of User Generated Content" (Kaplan and Haenlein 2010, 61). Generally, companies can use social media in two different ways: for communication with external stakeholders (e.g., via a company facebook page) or for internal interaction among employees (Leonardi, Huysman, and Steinfield 2013). Their use as tools within the company is referred to as "enterprise 2.0" (McAfee 2006) and the associated software is predominantly called ESM (Brzozowski, Sandholm, and Hogg 2009). Leonardi et al. (2013, 2) condense the characteristics of ESM into the following definition: ESM are "web-based platforms that allow workers to (1) communicate messages with specific coworkers or broadcast messages to everyone in the organization; (2) explicitly indicate or implicitly reveal particular coworkers as communication partners; (3) post, edit, and sort text and files linked to themselves or others; and (4) view the messages, connections, text, and files communicated, posted, edited and sorted by anyone else in the organization at any time of their choosing." This definition, however, captures only general capabilities of enterprise social media applications. A further examination is needed to gain a comprehensive and more differentiated view of practices and benefits of blogs, social networks, and wikis within corporate intranets.

Enterprises expect a number of benefits from ESM use: Preservation and reuse of knowledge stored in organizational and departmental wikis (Stocker et al. 2012), communication among employees beyond organizational hierarchies and across distant locations leading to more new ideas and creativity, feelings of less distance to top management in the case of internal CEO or similar blogs (cf. Kosonen, Henttonen, and Ellonen 2007), quick help from peers in discussion groups (within social networks or in separate applications) and so on. Of course, usually not all goals will be pursued at the same time and the goals will be more specific. However, the question whether employees will make these organizational goals their own goals remains unanswered. To address this issue, we take an employee's perspective of uses and benefits of ESM. Some insights to answer this question can be gained from Internet social media. However, these insights must be carefully scrutinized since ESM is likely to be different in terms of practices and individual benefits (Richter, Riemer, and vom Brocke 2011). While social media users in the private realm spend their spare time to publish and consume content mostly for hedonic purposes (Lin and Lu 2011), employees usually use them during work time and are expected to generate work-related benefits for them and the company. Even if explicit organizational rules for their use may not exist, employees will usually restrict themselves in terms of scope, tone (e.g., no flaming), and some other aspects when they contribute content. They will usually adhere to (perceived) corporate culture. Finally, due to the competitive situation among employees, less altruism can be expected within an enterprise than on the Internet where contributors often want to help mostly anonymous, less experienced or less knowledgeable users. All these circumstances may prevent ESM from growth or lead to their (de facto) death. It has also been reported that employees may refuse to participate in ESM as a result of time pressure (Brzozowski, Sandholm, and Hogg 2009). Another important difference between the use of social media in the private realm and at the work place is that the initial decision whether to adopt the software or not has already been made by organizational instances before it comes to individual adoption of ESM (Stafford, Stafford, and Schkade 2004). While standard software which directly supports business relevant processes (e.g., ERP-software) is procured to fulfil pre-defined tasks, ESM users have to discover how to make use of this software innovation because participation is usually open and voluntary (Chen and Hung 2010; Wasko and Faraj 2005). All these differences necessitate an analysis of why corporate users might want to use ESM.

2.2 Uses and Gratifications of Enterprise Social Media

The frame of uses and gratifications (U&G) can help to conceptualize the different uses of blogs, social networks, and wikis in the enterprise. The U&G approach attempts to explain behavioral patterns of media use and their underlying motivation. U&G is based on the assumption that individuals are actively involved in seeking out specific media to accomplish specific goals and satisfy specific needs (Katz, Blumler, and Gurevitch 1973; Rubin 1986). This approach provides the basis to identify the main support functions of ESM from the perspective of employees. U&G have been extensively researched for social media in the private realm finding a broad range of motivations including social and affection needs, needs to vent negative feelings, recognition, entertainment, and cognitive needs (Leung 2013; Leung 2009). Within enterprises, the benefits from social media participation are expected to be different (Richter, Riemer, and vom Brocke 2011) but they are still vague. Given the large number of application possibilities and the above mentioned differences regarding their technological characteristics, ESM cannot be treated as a single entity when analyzing their users' motivations and uses. Therefore, we derive uses and gratifications separately for blogs, social networks, and wikis at the workplace from extant literature on social media use in enterprises and in the private realm. Hereby, we emphasize the motives of participants who publish and consume content in line with the research focus.

Blogs satisfy various needs of authors and readers on the Internet. Often, blogs are strongly influenced by the author's personality and represent a place to express one's opinion and share it with the public (Nardi et al. 2004). In this light, prior research found blogs to be mostly used as a diary, catharsis, muse, or as a commentary on politics or society (Nardi et al. 2004; Kaye 2005). Additionally, previous studies found that private blogging is important to build up relational benefits such as person perception, reciprocity and the strengthening of social ties (Chai, Das, and Rao 2011; Hsu and Lin 2008; Zhao and Rosson 2009). Research on motives to blog in corporate intranets reflects these two focal points, however, with slightly different emphases. Information sharing and dissemination remains one of the most important motives for actively operating a blog (Turban, Bolloju, and Liang 2011; Paroutis and Al Saleh 2009) but the focus shifts away from personal statements towards the dissemination of work related information – for example through a CEO's blog (cf. Denyer, Parry, and Flowers 2011). Relational benefits have also been identified as a motive in studies on intranet blog usage (Turban, Bolloju, and Liang 2011; Günther et al. 2009; Back and Koch 2011). Therefore, building up reputation and relationships through communication is a second, albeit slightly less important support function of blogs in enterprises.

In social networks, it is all about building and maintaining relationships – in the private sphere as well as in the workplace. Keeping in touch with friends, making new friends, maintaining interpersonal connectivity are consistently mentioned as the main reasons to participate in Internet social networks (e.g., Raacke and Bonds-Raacke 2008; Kietzmann et al. 2011; Cheung, Chiu, and Lee 2011). Research on enterprise social networks likewise emphasizes relationship management (which includes both maintaining relationships and connecting with new people) as the most important factor (Back and Koch 2011; DiMicco et al. 2008) and adds communication support and information sharing as further facets which entice employees to use enterprise social networks (Turban, Bolloju, and Liang 2011). However, information dissemination in social networks is mostly limited to the direct social network of the author instead of the public as it is the case with blogs.

Wikis have the longest tradition of social media applications within enterprises. In contrast to social networks and blogs, wikis were originally developed for professional use as a knowledge management system (Leuf and Cunningham 2008). However, it was mostly after they became popular on the Internet (esp. Wikipedia.org) that enterprises rediscovered them as a simple and cheap tool for knowledge management, often after bad experiences with more powerful but more complex and more expensive tools. They are especially often used as a repository for unstructured knowledge. The comparatively long experience with wikis in corporate intranets has led to a profound body of research examining motives of wiki use. One factor stands out across all studies on this topic: knowledge collaboration (e.g., Turban, Bolloju, and Liang 2011; Bughin and Manyika 2007; Levy 2009). Employees use wikis to accumulate and improve knowledge incrementally and reuse it later. Sometimes, wikis are also used as a simple repository for unstructured knowledge, e.g., to track who has done what and when in a project. While content published in blogs and social networks represents the author's opinion, wikis help to externalize knowledge and jointly develop objectified knowledge bases (cf. Schultze 2000) rather than to publish subjective statements. Persistent knowledge in wikis can be regarded verified since the power afforded to users to delete (parts of) articles or edit them reduces the information clutter (Wagner 2004) and lets only information survive that the wiki community agrees upon. The mentioned U&G of ESM have to be considered when formulating hypotheses on drivers of ESM adoption. They are summarized in Table 1 with a qualitative evaluation of their fit with ESM.

Table 1 Uses and gratifications of enterprise social media

Uses / *Medium*	*Information Dissemination & Sharing*	*Relationships & Communication*	*Knowledge Collaboration*
Blogs	++	+	o
Social Networks	+	++	o
Wikis	+	o	++

Notes: ++ = well suited, + = suited, o = not suited

This approach complements traditional technology acceptance research (e.g., Davis 1989; Venkatesh et al. 2003) since it connects the motivational perspective of U&G with technological and individual characteristics considered in TAM and UTAUT. Therefore, we adapt the baseline hypotheses from adoption research on collaboration technologies and elaborate the differences for blogs, social networks, and wikis using the framework developed in this section.

3. MODEL DEVELOPMENT

In general, individuals are motivated to make use of information systems by external and internal factors (Stafford, Stafford, and Schkade 2004; Compeau and Higgins 1995; Davis, Bagozzi, and Warshaw 1992). Whereas situational characteristics are external drivers affecting the use of information systems, perceived technological and individual characteristics represent internal factors. Task characteristics cannot be solely assigned to one of these motivations because users perceive a task-technology interaction (cf. Zigurs and Buckland 1998). Although external factors such as social influence and facilitating conditions are also part of models such as UTAUT, we want to put emphasize on the internal factors (technological and individual characteristics) and applications use because they interact directly with ESM rather than reflecting organizational rumors about a software which has not yet been implemented at the time of the survey. Furthermore, technological and individual factors are assumed to make a significant contribution within ESM adoption research as parts of the TOSI (technological, organizational, social, individual) factors suggested by Chin et al. (2015). In a first step, we develop baseline hypotheses (H_{Bx}) by identifying technological and individual drivers of ESM use specific to collaboration technologies (cf. Brown, Dennis, and Venkatesh 2010) and ESM (cf. Chin, Evans, and Choo 2015). However, models such as UTAUT, TAM, or TOSI cannot explain motivational differences for the use of different technologies. In a second step, we bridge this gap by explaining differences (H_{Dx}) between the influences of variables on intention to use for blogs, social networks, and wikis based on the presented U&G framework for ESM. Thus, we posit that the identified U&G affect the strength of the relationships between technological and individual characteristics and intention to use across ESM applications. We expect this to function in such a way, that when U&G of a certain ESM tool fit well with a technological or individual characteristic, the influence of this particular characteristic on the intention to use will be strong. The research model developed in the following sections is shown in Figure 1.

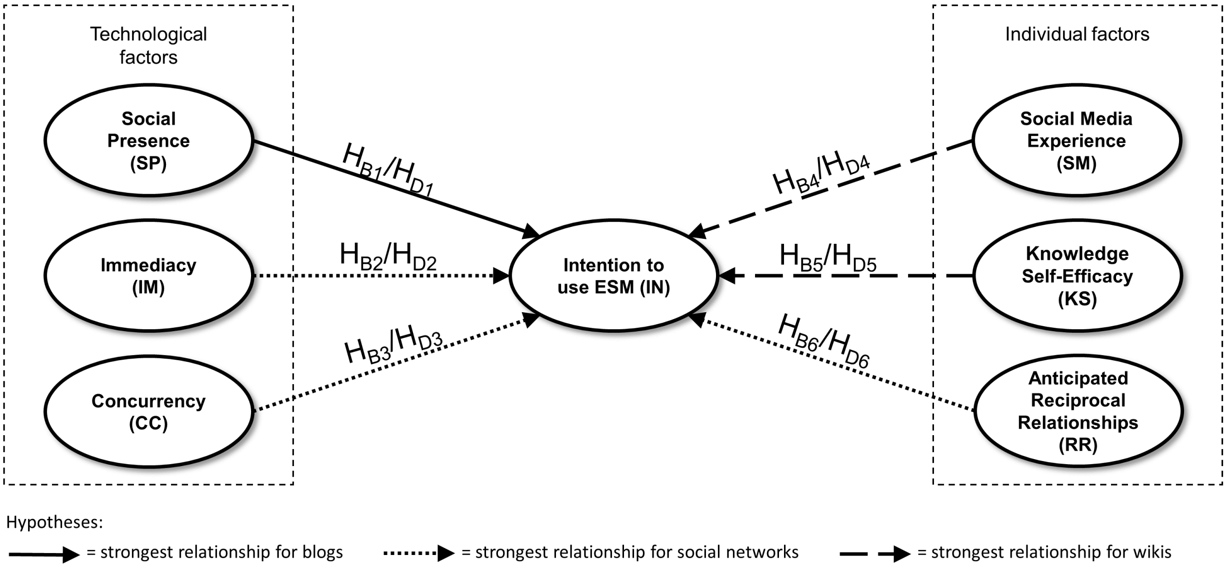

Figure 1 Research Model

The operationalization of the dependent variable differs in technology acceptance research. A wide body of literature employs behavioral intention as the dependent variable based on the assumption that it is a strong predictor of future usage (e.g., Agarwal and Prasad 1997; Wang, Wu, and Wang 2009; Karahanna, Straub, and Chervany 1999). While results from various empirical studies strongly support this assumption (e.g., Venkatesh, 2000; Davis, 1989), other studies conclude that greater explanatory power can be achieved by including use behavior as the dependent variable (e.g., Venkatesh and Bala 2008). In this study, we examine individual adoption of ESM in the pre-implementation phase. In this case, the intention to adopt needs to be the dependent variable (Karahanna, Straub, and Chervany 1999) to avoid possible incorrect inferences (cf. Wang, Wu, and Wang 2009).

3.1 Technology characteristics

Technology characteristics can be considered from an objective and subjective perspective. Viewed objectively, physical characteristics of a technology, e.g., average response time of an application in a given system environment, are innate and equal for all users. However, every user has a subjective perception of a technology (Fulk 1993), e.g., whether it operates slow or quickly, based on personality and prior experiences. This means that objective characteristics are stable, while individual perceptions differ among users and are subject to change over time (Carlson and Zmud 1993). To understand individual behavior, it is, therefore, important to assess subjective technology characteristics as perceived by users. Brown et al. (2010) identify three factors specific to collaboration technology which affect behavioral intention through performance and effort expectancy: social presence, immediacy of communication, and concurrency.

Social presence is the "degree of salience of the other person in the interaction and the consequent salience of the interpersonal relationship" (Short, Williams, and Christie 1976, 65). Social presence thus describes the extent to which a person is perceived by its interaction partners as a real person when using the communication medium. While personal face-to-face communication has the highest possible social presence (respectively media richness, (Daft and Lengel 1986)), deviations from personal communication always result in a decrease in naturalness of communication (Kock 2004). ESM applications with a high social presence are, therefore, more similar to personal communication and more natural for interaction partners.

H_{B1}: *Social presence has a positive effect on the behavioral intention to use ESM.*

Research on social presence suggests that people assess the social presence necessary to solve a task and search for a medium which provides a sufficient amount of social presence (Short, Williams, and Christie 1976). Rich media (higher social presence) are preferred in uncertain or ambiguous situations (Straub and Karahanna 1998) or for tasks that require a high level of trust (Gefen and Straub 2004). Sharing objective knowledge via wikis requires neither a huge amount of trust nor does it take place under uncertain or ambiguous conditions. Peers can review and improve content easily and prevent the wiki from becoming unreliable. In contrast, enterprise blogs and social networks are mostly used to spread subjective information and to maintain relationships. While the target audience in social networks is a group of connected colleagues, blog entries can reach a wide anonymous audience. Thus, a high social presence is a prerequisite to be perceived trustworthy by readers and, associated therewith, persuade the audience. Therefore, we argue that:

H_{D1}: *The effect of social presence on the behavioral intention to use ESM will be stronger for blogs than for social networks and wikis.*

Immediacy of communication is defined as "the extent to which a collaboration technology enables the user to quickly communicate with others" (Brown, Dennis, and Venkatesh 2010, 20). The construct immediacy of communication goes back to (Straub and Karahanna 1998) where recipient availability in the context of media choice for knowledge workers was studied. Immediacy depends on both, technological capabilities and the individual use behavior (Brown, Dennis, and Venkatesh 2010). In line with the U&G assumption, the task closure model suggests that people actively seek for a medium to fit their needs, or more precisely, people choose the collaboration technology based on its ability to communicate quickly (Straub and Karahanna 1998). The U&G framework for ESM identifies communication uses as the main support function of enterprise social networks. Built in functionalities such as instant messaging, profile updates, or the possibility to leave comments on various kinds of published content provide users with tools to communicate quickly with single or multiple peers. In contrast, communication via blogs and wikis mostly knows no direct addressees. Instead, it works asynchronously on the principle of publishing content and waiting for a response. Therefore, we hypothesize:

H_{B2}: *Immediacy has a positive effect on the behavioral intention to use ESM.*

H_{D2}: *The effect of immediacy on the behavioral intention to use ESM will be stronger for social networks, as compared to blogs and wikis.*

Concurrency refers to "the ability of a collaboration technology to enable an individual to perform other tasks at the same time as using the technology" (Brown, Dennis, and Venkatesh 2010, 21). These activities may be either the parallel use of other technology features or the execution of other tasks within the same technology (Rennecker, Dennis, and Hansen 2006). Social networks are the only technology covered in this study which provides the technical capability to perform multiple tasks simultaneously within the technology. For example, one can engage in multiple chat sessions or chat while searching for new friends. Additionally, the main uses of social networks (relationship management and communication) are intellectually usually less demanding than writing blog posts or creating knowledge in wikis. Therefore, we assume that the provision of applications, which allow performing multiple activities simultaneously, increases the intention to use an ESM technology and that the impact of concurrency is the strongest for social networks.

H_{B3}: *Concurrency has a positive effect on the behavioral intention to use ESM.*

H_{D3}: *The effect of concurrency on the behavioral intention to use ESM will be stronger for social networks than for blogs and wikis.*

3.2 Individual Characteristics

Individual characteristics are assumed to influence the behavioral intention to use ESM since not only different perceptions of the software features but also different personal traits and expectations affect the decisions whether to adopt a technology (Dennis, Wixom, and Vandenberg 2001; Dennis et al. 1988). We adjust the factors belonging to individual characteristics in consideration of the research context as demanded by Brown et al. (2010). Thereby, we focus on three constructs drawn from research on social media and knowledge sharing that are likely to have strong effects on the intention to use ESM.

Social media experience in a private realm is related to the non-commercial use of blogs, wikis, and social networks. Nowadays, social media usage has become ubiquitous for many employees in their private environment and they are familiar with these technologies. As described in the previous section, ESM still contain the core characteristics of social media on the Internet. Although both versions differ in their U&G, the handling is similar. In general, the choice and use of a technology are influenced by the experience with it (Carlson and Zmud 1993). If employees have no experience with ESM, they can resort to their experience with Internet social media which serves as an anchor influencing the attitude towards the new technology (cf. Venkatesh 2000). Since hedonic social media are primarily driven by enjoyment (Lin and Lu 2011), we assume that experiences with social media in a private realm lead to a higher intention to use ESM applications.

H_{B4}: *A user's social media experience in the private realm has a positive effect on the behavioral intention to use ESM.*

The difference between the importance of private social media experience as a predictor of intention to use cannot be resolved using the U&G framework. Instead, we elaborate on the handling of blogs, social networks, and wikis. Content can be intuitively created and published thanks to "what you see is what you get" (WYSIWIG) editors in blogs and social networks on the Internet and intranet (Schwartz et al. 2004; Harrison and Thomas 2009). Although some wikis already provide WYSIWIG editors, wiki content is predominantly edited using a simplified form of a mark-up language since this lets the user exploit the full functionality of wikis (Augar, Raitman, and Zhou 2004; Mader 2008). However, the wiki mark-up language is seen as complex and confusing for first time users who may be overwhelmed by the knowledge needed (e.g., syntax) to contribute content (Augar, Raitman, and Zhou 2004; Holtzblatt, Damianos, and Weiss 2010). Thus, prior experience with social media in the private realm can help to mitigate entry barriers, especially for wikis.

H_{D4}: *The effect of private social media experience on the behavioral intention to use ESM will be stronger for wikis than for blogs and social networks.*

Knowledge self-efficacy is a further factor that can influence the intention to use of ESM. Self-efficacy is described as „beliefs in one's capabilities to organize and execute the courses of action required to manage prospective situations" (Bandura 1995, 2). Hence, knowledge self-efficacy is the belief that one can master future situations by using one's own knowledge to accomplish job related tasks (Constant, Sproull, and Kiesler 1996) For the purposes of ESM as tools of knowledge management, this means that employees with a high knowledge self-efficacy prefer using them to share their knowledge more frequently (Kankanhalli, Tan, and Wei 2005). People who do not believe in their capabilities, however, are afraid that the content they publish may not be important, accurate, or relevant to a specific issue (Ardichvili, Page, and Wentling 2003).

H_{B5}: *Knowledge self-efficacy has a positive effect on the behavioral intention to use ESM.*

Knowledge collaboration was identified as the major support function of enterprise wikis. While users may want to share their opinions without regard of reliability and relevance for communication purposes (as in blogs and social networks), enterprise wikis are used as electronic knowledge repositories with the aim of being a reliable knowledge base. Importance, accuracy, and relevance play an important role here. Thus, we hypothesize:

H_{D5}: *The effect of knowledge self-efficacy on the behavioral intention to use ESM will be stronger for wikis than for blogs and social networks.*

Anticipated reciprocal relationships are defined as “the degree to which one believes one can improve mutual relationships with others through one’s knowledge sharing” (Bock et al. 2005, 107). It has been shown that the attitude towards an active participation in knowledge management systems depends primarily on the anticipated reciprocal relationships (Bock et al. 2005). The use of social media tools within the company can help employees to network and build relationships more efficiently because they can identify colleagues with same interests or valuable job-related information. Since these relationships are directly observable through contact lists in social networks, web links within the blogosphere and the display of author names in wikis, we assume that anticipated reciprocal relationships positively influence active ESM use intention.

H_{B6}: *The anticipation of future reciprocal relationships has a positive effect on the behavioral intention to use ESM.*

It lies in the very nature of enterprise social networks to explicitly show relationships between people. Once added as “friends”, other people remain in the users social network (often called friends list) until the relationship is terminated by one side. This social network can lever for every node in it benefits of potential collaboration, the so called social capital (cf. Ellison, Steinfield, and Lampe 2007). While in enterprise social networks relationships are easily built up, maintained, and highly visible in the friend list, non-contributing users of blogs and wikis can hide behind their anonymity leaving contributing users of these technologies in doubt if there is an audience willing to get involved in a social exchange.

H_{D6}: *The effect of anticipated reciprocal relationships on the behavioral intention to use ESM will be stronger for social networks than for blogs and wikis.*

4. RESEARCH METHODOLOGY

4.1 Instruments

Each model variable is measured by multiple items. Items are drawn from proven and reliable scales and customized in consideration of the specific research area. The scales for social presence, concurrency, intention to participate actively, private social media experience, and immediacy of communication are based on Brown et al. (2010) and were tailored to the research context. The items of knowledge self-efficacy are adapted from Kankanhalli et al. (2005) and the scale for anticipated reciprocal relationships is drawn from (Bock et al. 2005). All above-mentioned constructs are measured reflectively on a seven-point Likert scale with the anchors being strongly disagree (1) and strongly agree (7). Only social media experience in the private realm has been modelled as a formative construct since it fits all criteria of a formative measurement model according to (Jarvis et al. 2003). The selection of scales, the questionnaire design, and the timing of the survey was discussed with five experts from academia and the company where the study was conducted. Minor amendments were implemented according to their feedback. The final item set is shown in the appendix.

4.2 Participants and Data Collection Procedure

A field study was conducted in German locations of an international ICT company after the procurement decision of an enterprise-wide social media platform has been made but before its implementation. The ICT sector was chosen since empirical data shows that large companies within this branch are often early adaptors of ESM (Saldanha and Krishnan 2012). An online survey that reached employees at several locations and in different business units was used to test the presented research model. 217 participants completed the online survey (at 382 page views). The questionnaire wording was adjusted for each of the three technologies. One of the three questionnaires was randomly assigned to participants aiming at the same number for each version. The resulting data sets have been inspected for missing values, processing time, and answer patterns. 29 records had to be excluded for these reasons. The revised sample contains 188 responses (blogs: n = 61, social networks: n = 64, wikis: n = 63) of which 42.6% were female respondents, 51.1% male and 6.4% skipped the question on gender. The average age of the participants is 35.5 years (SD = 9.3) while the youngest participating employee was 20 years old and the oldest participant was 59 years old. Age and gender distributions nearly mirror their distributions within the whole company, which indicates that no non-response bias occurred with respect to these demographics.

4.3 Data Analysis

Partial least squares (PLS) are used to compute the research model. PLS can handle small sample sizes, non-normally distributed variables, and is able to calculate reflective and formative indicators simultaneously (Hair et al. 2013). The data sets of the studies on blogs, wikis, and social networks were calculated separately using SmartPLS 3.2 (Ringle, Wende, and Becker 2015). We perform the significance tests using t-values resulting from the bias corrected and accelerated bootstrapping procedure (5000 resamples).

In a first step, we evaluate the quality of measurement models before turning towards the structural model. For this purpose, we assess the criteria indicator reliability, composite reliability, convergent and discriminant validity (Henseler and Fassott 2010). Indicator reliability is expressed by the outer component loadings calculated by SmartPLS and should surpass the value of 0.7. The more important composite reliability was calculated by the criterion internal consistency reliability (ICR) instead of Cronbach's alpha since it uses weighted item loadings and is, therefore, considered a better reliability measure (Fornell and Larcker 1981; Chin and Gopal 1995). The criterion score of 0,7 was adopted as recommended by Nunnally & Bernstein (1994). Average variance extracted (AVE) has been suggested as the measure to assess convergent validity (Fornell and Larcker 1981). AVE should exceed 0.5 to guarantee sufficient convergent validity. The discriminant validity is assessed in a two-step process. First, we check that the square root of AVE of a latent variable is higher than any correlation of these variables with any other construct in this model (Fornell and Larcker 1981). As a second criterion, we look at item loadings and cross-loadings to make sure that items are associated more highly with their theoretically intended construct than any other construct (W. W. Chin 1998). The formative measurement model for social media experience is assessed by examining the significance of indicator weights and multicollinearity (W. W. Chin 1998; Diamantopoulos and Winklhofer 2001). The variance inflation factor (VIF) is used to measure multicollinearity and should not surpass the value of 10 (Reinartz, Haenlein, and Henseler 2009).

5. RESULTS

5.1 Measurement Models

After dropping the item KS3 due to consistently low factor loadings across the studies, indicator reliability is achieved. ICR scores ranging from 0.81 to 0.96 suggest a strong composite reliability. A strong convergent validity is indicated by AVE scores above 0.5 for all variables and acceptable discriminant validity is shown by the square root of AVE exceeding the correlations with other variables (see Table 2). In addition, the consideration of item loadings and cross-loadings enhances the impression of good discriminant validity.

The items WE2 and WE3 for blogs, WE1 and WE2 for social networks, and WE1 and WE2 for wikis exhibit non-significant ($p > 0.1$) indicator weights. However, indicators with a lower contribution can be interpreted as absolutely but not relatively relevant and should remain in the model under the conditions that (1) the bivariate correlation is high and (2) they cover distinct facets of the respective variable (Cenfetelli and Bassellier 2009). All above-mentioned items were kept in the model since they fulfil both criteria. The VIF scores of social media experience are 2.43 for blogs, 1.25 for social networks and 1.20 for wikis. They lie well under the recommended upper limit and indicate low multicollinearity.

Since dependent and independent variables are measured using survey data, we checked the data sets for common method bias (CMB). For this, Harman's single-factor test was employed. In the presence of a substantial amount of common method variance (CMV) one factor would emerge from a factor analysis or a single factor would account for the majority of the covariance of all measured variables (Podsakoff et al. 2003). CMV was tested across the studies because the data for blogs, social networks, and wikis were measured using the same variables and almost identical items. A single factor accounted for 38 percent of the variance suggesting that CMB is not an issue in this sample.

Table 2 ICRs, AVEs, average (AVG), standard deviations (SD), and correlations

Blogs	*ICR*	*VIF*	*AVE*	*AVG*	*SP*	*IM*	*CC*	*SM*	*KS*	*RR*	*INT*
SP	0.93		0.83	3.81	**0.91**						
IM	0.91		0.76	4.01	0.53	**0.87**					
CC	0.96		0.88	3.32	0.55	0.73	**0.94**				
SM		2.43		4.51	0.61	0.69	0.68				
KS	0.81		0.63	5.05	0.34	0.32	0.19	0.30	**0.79**		
RR	0.93		0.74	4.40	0.53	0.61	0.50	0.50	0.36	**0.86**	
INT	0.95		0.86	3,44	0.59	0.67	0.48	0.63	0.22	0.54	**0.93**

Social networks	*ICR*		*AVE*	*AVG*	*SP*	*IM*	*CC*	*SM*	*KS*	*RR*	*INT*
SP	0.93		0.82	4.63	**0.90**						
IM	0.87		0.69	5.41	0.59	**0.83**					
CC	0.95		0.86	4.53	0.50	0.62	**0.93**				
SM		1.25		4.69	0.37	0.36	0.36				
KS	0.82		0.62	5.22	0.20	0.17	-0.04	0.12	**0.79**		
RR	0.93		0.73	4.75	0.60	0.53	0.34	0.34	0.18	**0.85**	
INT	0.95		0.85	5.09	0.60	0.52	0.48	0.48	0.22	0.58	**0.92**

Wikis	*ICR*		*AVE*	*AVG*	*SP*	*IM*	*CC*	*SM*	*KS*	*RR*	*INT*
SP	0.91		0.78	3.70	**0.88**						
IM	0.85		0.67	3.35	0.42	**0.82**					
CC	0.90		0.75	3.20	0.39	0.53	**0.87**				
SM		1.20		4.54	0.00	0.23	0.20				
KS	0.85		0.65	5.11	0.03	0.11	-0.03	-0.05	**0.81**		
RR	0.92		0.71	4.37	0.47	0.32	0.30	0.28	0.27	**0.84**	
INT	0.96		0.90	4.64	0.12	0.47	0.19	0.30	0.40	0.08	**0.95**

5.2 Structural Model and Hypotheses

As shown in Table 3, the six factors affect the three examined technologies differently. Social presence, immediacy, and social media experience in the private realm are significant predictors of intention to use blogs, thus supporting the hypotheses H_{B1}, H_{B2}, and H_{B4}. Concurrency has a significant negative impact on the dependent variable in the study on blogs. For social networks, social presence, concurrency, private social media experience, knowledge self-efficacy, and anticipated reciprocal relationships are drivers of intention to use confirming hypotheses H_{B1}, H_{B3}, H_{B4}, H_{B5}, and H_{B6}. Finally, the significant positive impacts of immediacy, private social media experience, and knowledge self-efficacy confirm the hypotheses H_{B2}, H_{B4}, and H_{B5} for wikis. The effect of reciprocal relationships on intention to use wikis is significantly negative rejecting H_{B6}. The model explains 58% of the variance in intention to use in the study on blogs, 52% in the study on social networks, and 45% for wikis.

A comparison of coefficients by columns shows whether the corresponding hypotheses H_{D1-6} are confirmed. This is the fact in all cases with the exception of H_{D2} which relates to immediacy. Immediacy of communication has both a strong significant effect on intention to use blogs (β = 0.47) and wikis (β = 0.43) but does not significantly affect intention to use social networks (β = 0.03). Thus, hypothesis H_{D2} is rejected.

Table 3 Coefficients of determination, path coefficients, and significance levels

				H_{D1}	H_{D2}	H_{D3}	H_{D4}	H_{D5}	H_{D6}
	Study	Criterion	intention to use	SP	IM	CC	SM	KS	RR
H_{B1-6}	Blogs	R^2	0.58						
		Path coefficient		**0.27****	**0.47*****	**-0.25***	**0.28****	-0.10	0.13
H_{B1-6}	Social networks	R^2	0.52						
		Path coefficient		**0.23****	0.03	**0.18***	**0.22***	**0.10****	**0.28*****
H_{B1-6}	Wikis	R^2	0.45						
		Path coefficient		0.06	**0.43*****	-0.03	**0.30***	**0.44*****	**-0.28****
H_{Dx} confirmed?				yes	no	yes	yes	yes	yes

Notes: * p < 0.1; ** p < 0.05; *** p < 0.01

6. DISCUSSION

This paper has two key objectives: First, we build a model of ESM adoption considering technological and individual characteristics from research on collaboration technology and knowledge sharing. The characteristics are adapted for this purpose. Second, we elaborate on the differences between enterprise blogs, social networks, and wikis with respect to users' U&G.

The results show partial support for the baseline model and substantial differences between the applications. Although the explained variances reach sufficient levels between 45% and 58%, only some predictors had a significant positive influence on intention to use (three for blogs and wikis and five for social networks). Among the rejected hypotheses two stand out: while almost all unsupported hypotheses have insignificant path coefficients, the influences of concurrency on intention to use blogs and reciprocal relationships on intention to use wikis are significant but negative. While we expected that concurrently working on blogs and other work related tasks might be more difficult than simultaneously using a social network or a wiki, the negative path coefficient of concurrency on intention to use blogs suggests that blog usage even prevents performing concurrent tasks. This might be caused by both the type and the size of the content. A blog is a medium to share opinions and anecdotes rather than facts. Such anecdotes have to be narrated properly for the blog instead of typing in a short message in a social network or pasting facts in a wiki. Hence, the creation of comparatively long articles and the corresponding editorial work does not go hand in hand with simultaneous tasks. To resolve the counterintuitive but interesting result in the study on wikis one may look at the rate of active contribution by wiki users in general. Studies report that below 2.5% of wiki users contribute content on the Internet and in organizational contexts (e.g., Ebner et al., 2008). While this low contribution rate still translates to an absolute number of about 1.8 million active editors of Wikipedia (Wikipedia 2014), contributors to a corporate wiki with several thousand readers may still be less than 100. Thus, with these figures in mind, some employees may want to contribute to wikis, but they do not expect their colleagues to do the same. The contribution by the few is probably more guided by altruistic motives than by expectation of reciprocity (Hester 2011; Prasarnphanich and Wagner 2009). In summary, our results indicate that this may turn employees interested in building reciprocal relationships away from wikis and towards, for example, enterprise social networks.

The results for the hypotheses concerning the differences between blogs, social networks, and wikis (H_{D1}-H_{D6}) mostly confirm our hypotheses. Only hypothesis H_{D2} implying that immediacy has a stronger effect on intention to use in social networks than for blogs and wikis was not supported. Although communication support is one of the major functions of social networks, the extent to which users perceive that social networks enable them to quickly interact with other employees does not affect intention to use significantly. Judging from average immediacy scores, people perceive social networks as a quicker mean for communication than blogs and wikis but our results indicate that immediacy is not their primary driver to participate actively. It must be the possibilities of asynchronous communication and automatic updates of contact lists when contacts change their data, easy profile updates, and easy posting to all contacts that drive the use of social networks rather than immediacy. This may be compatible with the observation that other applications have become more popular for immediate exchange in the private realm (e.g., WhatsApp or Twitter). In the same time, this finding may partly explain why some companies replace asynchronous communication via email by features of social networks (Gartner 2010; Skeels and Grudin 2009).

6.1 Theoretical Contribution

A deep understanding of technological and individual determinants influencing the technology adoption process is currently one of the most mature streams in research on information systems (Benbasat and Barki 2007; Venkatesh, Davis, and Morris 2007). This study seeks to advance knowledge within this stream with two important contributions.

First, we identify technological and individual characteristics influencing technology adoption drawn from research on collaboration technology and knowledge repositories to build an integrative model of active ESM participation intention. Focus on specific technologies in IS adoption research has been considered a necessary next step (Venkatesh and Bala 2008). The results of our studies back up this necessity. Within an application class that is often treated as a single entity, significant differences between the drivers of participation arise. For IS decision-makers, little is gained by looking at broad-based studies covering multiple (even similar) technologies without differentiating them. The lack of detailed considerations of specific uses and technology characteristics can be misleading. Even if a group of technologies often referred to under a common headline such as ESM share deep underlying principles (e.g., user generated content) and handling characteristics (McAfee 2009), a joint consideration of multiple technologies with different U&G can be at best a preliminary approximation.

Second, we attempt to predict the differences between the drivers of participation by combining approaches from organizational and private adoption research. Studies based on TAM or UTAUT have usually focused on individual adoption of technological artefacts within enterprises under the premise that software is procured for a specific task. In contrast, the basic assumption of the U&G framework is that people search for a medium to accomplish a specific task as it fits them, not as conceived by technology promoters even if a technology has already been adopted by the organization for another task. Thus, the approach has been primarily employed for examinations of private and hedonic technology use (Stafford, Stafford, and Schkade 2004). Linking both approaches provides us with information about user intentions towards the use of corporate IS with vague pre-defined uses. Our results show that U&G have an effect on the strength of relationships between the introduced variables and intention to use and thereby indicate that considering the interplay between user, uses, and technology is a valuable methodology to predict the relative impact of adoption factors in comparison to other technologies.

6.2 Practical Implications

From a practical perspective, this study offers two important starting points for managerial implications. First, the identification of drivers of ESM adoption provides IS decision makers with information about technological and individual factors crucial for the initial individual use of ESM by employees. To increase their intention to use blogs, a particular focus should be laid on the ability to present oneself using visually rich content (e.g., via videos). To increase immediacy of blogs, a web-feed (e.g., RSS) should be provided to quickly inform blog followers about the new content. The same is true for wikis where a "wiki feed" can speed up knowledge exchange. In corporate wikis which are sometimes maintained by relatively small groups and devoted to a specific subject, wiki users often know each other and want to make the knowledge immediately and permanently available to everyone in the group, e.g., a project team. The intention to participate in social networks can be most efficiently increased by enabling users to continue other work while using ESM and to tie them stronger to functional business applications (e.g., ERP, CRM). Providing interfaces to standard software (e.g., by synchronizing contact lists from the social network with the mail program) can be also helpful.

Second, our study emphasizes the importance of a joint consideration of technological, individual, and use characteristics. Employees new to ESM should receive guidance and support consistent with their individual characteristics on how to benefit from the new technologies. While individuals who seek for a possibility to disclose their opinions to all employees should be advised to use blogs, people trying to increase their social capital (e.g., by connecting with experts) should use social networks. Wikis should be recommended to those who want to share their knowledge with peers. Support should be given to those employees who can benefit from ESM but lack the capabilities. This will help to decrease the potential reluctance of employees to use ESM (Turban, Bolloju, and Liang 2011) and prevent them from searching alternatives on the Internet (e.g., Facebook) which may result in data privacy risks. Therefore, rather than solely concentrating on the technological and individual characteristics, particular uses should always be kept in mind when implementing or further developing ESM. To lever the aforementioned advantages and simultaneously prevent the risks, IS procurement departments should scrutinize carefully how social media can be used by employees within the company, utilize the results of this examination to identify the most suitable technology, and deploy software that fits those needs.

7. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

The first limitation results from the selection of a sample within one company as the data basis of our work. This choice limits the generalizability and it must be assumed that the voluntary participation induces self-selection (Stanton 1998). Self-selection is accompanied by potentially different attitudes toward the technology and experiences in using them between participants and non-participants. Moreover, some empirical evidence suggests that size and sector of the company influence the employees' use of social media (Leibhammer and Weber 2008; Saldanha and Krishnan 2012). Since our study was conducted in a big multinational company in the ICT sector, future studies should examine whether the discovered relationships and differences between technologies also hold in small or medium-sized companies and outside of the ICT sector.

Due to strict data privacy policies and employee rights it was not possible to track actual use behavior in the post-implementation phase and to tie it to the respective data sets. Since behavioral intention does not necessarily correlate strongly with system usage (Wu and Du 2012), future research would benefit from supplementing these studies from the pre-implementation phase with a longitudinal approach that uncovers relationships between the intention to participate actively and actual posting and reading behavior.

Although the independent variables explain substantial parts of the variance in all three studies, the focus of the research model is on technological and individual characteristics excluding other views which may have an influence on the behavioral intention or show differences between blogs, social networks, and wikis. The presented model can serve as a starting point to integrate other perspectives such as influences of facilitating conditions and reference groups.

8. CONCLUSION

Extant literature provides only partial insights into ESM adoption mostly focusing on one particular application or ESM as an entity. This research expands knowledge on ESM adoption across multiple applications. For this, we focus on technological and individual drivers of ESM adoption by integrating variables drawn from research on collaboration technology and prior ESM research. Our model provides a comprehensive understanding of technological and individual factors affecting individual ESM adoption in the enterprise across technologies. To elaborate on the differences between blogs, social networks, and wikis, we applied the U&G lens. The framework allowed us to correctly predict the differences of factor influences on the intention to use the three applications as observed in three separate studies. This helps to understand the conjunction of individual and technological characteristics with uses and gratifications that users look for in specific applications.

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Appendix

Construct	*Items*
Social presence (SP) *Adapted from* (Brown, Dennis, and Venkatesh 2010)	SP1. Using blogs/wikis/social networks to interact with others creates a warm environment for communication. SP2. Using blogs/wikis/social networks to interact with others creates a sociable environment for communication SP3. Using blogs/wikis/social networks to interact with others creates a personal environment for communication.
Immediacy of communication (IC) *Adapted from* (Brown, Dennis, and Venkatesh 2010)	IC1: Blogs/wikis/social networks enable me to reach communication partners quickly. IC2: When I communicate with someone using blogs/wikis/social networks, they usually respond quickly. IC3: When someone communicates with me using blogs/wikis/social networks, I try to respond immediately.
Concurrency of communication (CC) *Adapted from* (Brown, Dennis, and Venkatesh 2010)	CC1: I can easily use blogs/wikis/social networks while participating in other activities. CC2: I can easily communicate using blogs/wikis/social networks while I am doing other things. CC3: I can use blogs/wikis/social networks while performing another task.
Social media experience (SM) *Adapted from* (Brown, Dennis, and Venkatesh 2010)	SM1: My experience with blogs is: None at all . . . Very extensive SM2: My experience with wikis is: None at all . . . Very extensive SM3: My experience with social networks is: None at all . . . Very Extensive
Knowledge self-efficacy (KS) *Adapted from* (Kankanhalli, Tan, and Wei 2005)	KS1: I have confidence in my ability to provide knowledge that others in my organization consider valuable. KS2: I have the expertise needed to provide valuable knowledge for my organization. KS3: It doesn't really make any difference whether I add to the knowledge others are likely to share. [reversed, dropped] KS4: Most other employees can provide more valuable knowledge than I can. [reversed]

Anticipated reciprocal relationships (RR) *Adapted from* (Bock et al. 2005)	RR1: My knowledge sharing would strengthen the ties between existing members in the organization and myself. RR2: My knowledge sharing would get me well-acquainted with new members in the organization. RR3: My knowledge sharing would expand the scope of my association with other members in the organization. RR4: My knowledge sharing would draw smooth cooperation from outstanding members in the future. RR5: My knowledge sharing would create strong relationships with members who have common interests in the organization.
Intention to use *Adapted from* (Brown, Dennis, and Venkatesh 2010)	IN1: I intend to read and write blog entries in the future. / I intend to read and write entries in wikis in the future. / I intend to use social networks and publish content in the future. IN2: I predict I would read and write blog in the in the future. / I predict I would read and write entries in wikis in the in the future. / I predict I would use social networks and publish content in the future. IN3: I plan to read and write blog in the in the future. / I plan to read and write entries in wikis in the in the future. / I plan to use social networks and publish content in the future.