Should We Take a Closer Look?
Extending Switching Theories from Singular Products to Complex Ecosystem Structures

Abstract
While previous research on software ecosystems (SECO) mostly focused on SECO providers or software developers, recent studies have begun to analyze the user perspective and try to explain switching behavior. However, SECOs are complex and consist of several components. Since current switching theories do not fully account for these complex structures, these need to be adapted. We expand the push-pull-mooring (PPM) framework to account for SECO components so as to obtain a more fine-grained understanding of why users decide to switch SECOs. We find that users' switching decisions are primarily governed by pull factors, while mooring and push factors also have significant but smaller impacts. Individual SECO components show differential impacts across all PPM constructs, which should be considered by researchers and practitioners. Beyond SECOs, we seek to break new ground for technology switching and (post-)adoption models to consider complex interactions between different systems and their components.

Keywords: Mobile OS Ecosystems, Ecosystem Components, User Switching Intentions, Push-pull-mooring Framework
Introduction

In recent years, smartphone sales have seen tremendous growth (IDC 2014). However, it is not only the smartphone, but also access to an entire software ecosystem (SECO) that users purchase and that presumably explains this success. A SECO is a complex system of different components, which create aggregated value for users. Building on the mobile operating system (OS) as the cornerstone of the SECO, an ever-expanding, connected network of different players has formed, ranging from application developers to accessory manufacturers. Mobile OS ecosystem providers such as Google or Apple often seek to harmonize usability and to enable automatic data-sharing across the different ecosystem components. For instance, Apple iCloud enables the automatic synchronization of calendars, contacts, and media across multiple devices and serves as a means to lock in users (Bloomberg 2011). The importance of mobile OS ecosystems and the compatibility between different ecosystem components might further increase along with their integration into higher-value goods, such as cars.

IS research often discusses SECOs, but mostly considers the perspectives of ecosystem providers or software developers, for instance discussing appropriate levels of control over the ecosystem or multihoming strategies for external vendors in the ecosystem (Landsman and Stremersch 2011; Maurer and Tiwana 2012). However, questions of user adoption and switching of ecosystems have long remained unanswered. Lin and Huang (2014) presented a first approach to explain users switching from one SECO to another, by employing the push-pull-mooring (PPM) framework and by using iPhones and Android phones as proxies for the entire SECO. However, examples from practice show that smartphones are not always a good proxy for measuring a SECO’s success and users’ loyalty to it. For instance, the massive emigration from the Blackberry ecosystem was assumed to have been caused mainly by a much lower availability of popular apps. Likewise, Apple’s success is often attributed to easy linkages with other complementary products and services from the Apple ecosystem (Hess and Matt 2013).

We therefore hold that it is not sufficient to use a single SECO component as representative of an entire ecosystem. Instead, it is essential to model the entire ecosystem, including its individual components in order to obtain a comprehensive understanding of users’ SECO switching decisions. Previous research has omitted this step, perhaps because it is difficult and cumbersome to integrate SECO components into switching models without questionnaires becoming too long. Our research seeks to close this research gap by extending the PPM framework to integrate the different mobile OS ecosystem components and to provide a comprehensive picture of SECO switching. Thus, our paper contributes to the current body of knowledge, not only by assessing the impacts of the different push, pull, and mooring factors, but also by accounting for the differential impacts of individual mobile OS ecosystem components (e.g., smartphones and apps). Beyond the scope of current research, our work also provides first guidance on how to adopt switching and adoption theories to allow for more complex products or systems and their components.

Our results are highly relevant for ecosystem providers to better understand their users’ underlying motivations for joining or leaving SECOs and for them to create targeted strategies.

Related Literature

Software Ecosystems

The notion of an ecosystem originated in the field of ecology. Bosch (2009) assigned software ecosystems to human ecosystems and distinguished between social and commercial ecosystems. Manikas and Hansen (2013) provided a systematic literature overview and identified three elements of a SECO: common software, business, and connecting relationship. Common software describes the existence of a common technology platform (Jansen et al. 2009) or some software solution (Bosch 2009), which is used by the actors of the ecosystem. Business indicates that actors conduct a form of business undertaking related to the software solution. It does not solely consider financial aspects, but also considers other elements such as benefits from involvement with other parties (Manikas and Hansen 2013). Connecting relationship reflects the symbiotic aspect of the software ecosystem, where numerous actors with different business models depend on each other while interacting on the software platform.

Bosch (2009) further distinguished between three SECO abstraction levels: end-user programming, application, and operating system. The latter include for instance Windows and Android, and became the
dominant organizational model in the software industry (Cusumano 2010). Its characteristics are pre-installation of the operating system (OS), domain independence, the provision of development tools, as well as optimization for standalone application deployment. Operating system-centric SECOs are the basis of our research. To deploy its entire functionality, the smartphone end-user device relies on a complex ecosystem around a mobile OS in which different participants interact on various technological layers (Basole and Karla 2011; Kenney and Pon 2011).

Despite substantial growth of research on SECOs in recent years, most studies focus on the perspectives of SECO platform providers (e.g., Jansen and Cusumano 2013) or software developers (e.g., Benlian et al. 2015). However, there is surprisingly little empirical evidence on users’ adoption, post-adoption, or switching decisions related to ecosystems. To date, research in these areas has mostly focused on singular products or services (Hsieh et al. 2012; Lai et al. 2012), but not on complex structures and dependencies between different components of these systems. However, more knowledge in this field is not only beneficial for SECO providers to better target their offers to their customers, research can also benefit from new insights to obtain a more comprehensive picture on user behavior related to SECOs.

### The Push-pull-mooring Framework to Explain Switching Intentions

Instead of solely focusing on the initial adoption of technologies, the continuous use of technologies has recently received more attention. Bhattacharjee (2001) examined post-acceptance variables without providing direct or deep insights into users’ switching intentions and the underlying drivers thereof. Furneaux and Wade (2010) proposed an IS discontinuance model with a focus on two aspects – dissatisfaction with the current information system and continuance inertia. They hypothesize that dissatisfaction and switching intentions rise owing to the existence of poor system performance, low system suitability (in meeting a company’s needs), and low system supportability (to maintain ongoing operations). However, the aspect of attractive choice alternatives and the resulting effects on the intention to switch were not incorporated in discontinuance theory. Thus, there is a lack of “an overarching theory that can tie together these switching predictors within a comprehensive framework” (Bhattacherjee and Park 2014).

A different approach resorts to IS migration theory, which describes migration as “the movement of a person (a migrant) between two places for a certain period of time” (Boyle et al. 1988). In marketing research, the PPM framework has gained broad acceptance. For instance, Bansal et al. (2005) provided a unified framework for examining consumers’ switching behavior that builds on the PPM framework. In IS, the PPM framework has recently seen numerous applications: For instance, Lui (2005) as well as Bhattacharjee and Park (2014) investigated infrastructure-related topics concerning mobile data services and cloud computing. Zengyan et al. (2009), Chang et al. (2014), Xu et al. (2014), and Yao et al. (2015) analyzed switching intentions in social networks using PPM. Hou et al. (2009) has used PPM to explain switching between online games; Ye and Potter (2011) focused on web browsers, and Hsieh et al. (2012) as well as Zhang et al. (2012) have employed it to analyze switching concerning blog service offerings.

Three striking arguments favor the application of the PPM framework in the context of SECOs. First, the migration decision process is similar to customers’ switching process. Second, the integration of negative aspects of the current state, the inclusion of attractive features of a potential alternative, as well as the consideration of personal, social, and cultural variables display a comprehensive picture of the factors underlying switching processes. Third, recent publications close to the software ecosystems context have built a strong basis and support the application of the PPM framework (Lin and Huang 2014).

### Research Model

#### Specification of the Mobile OS Ecosystem

Owing to the lack of a theoretical foundation for the operationalization of mobile OS ecosystems and their components, we pursued a two-step multimethod approach. We conducted qualitative interviews to understand how users comprehend mobile OS ecosystems, and we developed a quantitative research model and tested it with a survey.

We conducted 30 interviews (mostly with students), which provided 432 suitable quotes. For the analysis of the obtained data, we adopted quantitative content analysis (Mayring 2001), in which we generalized...
the quotes and assigned them to different SECO components. We reduced the generalized quotes and influence factors and compared them to existing IS constructs (such as switching costs). The qualitative interviews included questions about participants’ usage and switching behaviors and were loosely structured in accordance with the PPM framework. Owing to our focus on the user perspective, our main goal was to identify what SECO means to users, since this term’s meaning may be clear to researchers but not to users. Indeed, we realized that many participants were not familiar with the term and the concept of a SECO. Further, even if users were familiar with this term, our results revealed major differences in SECO composition and the importance that users attach to the different components. Therefore, after the first assessment of users’ understandings, we established a shared understanding of the term SECO, and decided to follow the classification by Bosch (2009). Thus, we defined SECO by its pre-installed mobile operating system as the SECO’s core as well as four additional elements: Smartphone, app stores and apps, interface with other devices, and accessories. While smartphone refers to the end-user device, app stores and apps comprise both pre-installed apps and apps available on public platforms. Interface with other devices describes a SECO’s ability to interact or exchange information with devices such as tablets or PCs. The importance of accessories can be seen due to the further development of the “Internet of Things” (e.g., in home automation or health-tracking), but also owing to the recent $3 billion acquisition of Beats by Apple. The overall formation of SECOs and the integration of different components is critical, since substantial network effects can accrue (Lin and Huang 2014). Also in other fields (such as video games), the importance of complementary products for a platform ecosystem’s success have been highlighted (Cenamor et al. 2013).

Adjustments to the PPM Framework and Hypotheses Development

Bansal et al. (2005) implemented the PPM framework as a higher-order model. These are applied such that constructs can “be operationalized at higher level of abstraction” (Hair et al. 2014). Certain adjustments were necessary to obtain an appropriate foundation for the adaptation of the PPM framework to the mobile OS ecosystem. In the following, for each of the first-order and second-order constructs, we describe the different influence factors and concluding hypotheses separately, ordered based on their classification as push, pull, or mooring factors. The conceptual research model is presented in Figure 1.

Figure 1. Overview of Research Model
Push Factors

Push factors “motivate people to leave the origin” (Stimson and Minnery 1998) and are further defined as “factors at the origin that are assumed to have a negative influence on the quality of life” (Moon 1995). In the context of IS, consumer switching can be motivated by a variety of influences such as experiences with and perceptions of a digital product or service.

Low satisfaction: Satisfaction is “the summary psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the customer's prior feelings about the consumption experience” (Oliver 1981). If users are satisfied, they tend to stay, while dissatisfied users form the intention to switch from the product or service to raise their satisfaction level (Bhattacherjee 2001). For IS research, (dis)satisfaction has been of great importance in order to explain user switching, for example in the context of email services (Kim et al. 2006) or web browsers (Ye et al. 2008). Studies that have applied the PPM framework and included satisfaction as a push factor found significant support for dissatisfaction as a migration accelerator (Bhattacherjee and Park 2014; Ye and Potter 2011; Zengyan et al. 2009; Zhang et al. 2012). Resulting low satisfaction with the SECO will be considered as a push factor, and we argue:

\[ H_{1a}: \text{Low satisfaction with the SECO positively influences the push factor.} \]

Low quality: In migration theory, quality of life considers physical or economic aspects of an individual's origin (Bansal et al. 2005). Zeithaml et al. (1996) showed that perceived inferior experiences with service quality led to unfavorable behavioral intentions for vendors, such as switching to other companies. Bansal et al. (2005) demonstrated the significance of quality as a push factor in PPM. Our interviewees stated that poor quality of the whole ecosystem but also of single components thereof raise their intention to switch from a SECO. Especially system stability seemed to be important to users in this respect. Thus, low quality is considered as a push factor, and we predict a positive influence on switching behavior. We hypothesize:

\[ H_{1b}: \text{Low SECO quality positively influences the push factor.} \]

Low trust: Trust is key to sellers of products and services in order to be able to attract new customers or retain existing ones. Morgan and Hunt (1994) understand trust as “the consumer's belief that the seller will fulfill promises” (Bansal et al. 2005). In IS and e-commerce, trust is defined as “a set of beliefs about the trustworthiness of an Internet Vendor” (Kim and Gupta 2012). Owing to the importance of trust in online environments, many research streams identify trust as a central concept of explaining ongoing online customer relationships. Among these studies, McKnight et al. (2002) developed a web trust model and conceptualized trust as trusting beliefs that formed trusting intentions and ultimately led to trust-related behavior. Gefen et al. (2003) combined trust and the Technology Acceptance Model (TAM) to highlight trust in both online sellers and the provided technology. Trust has also been examined in the context of technology artifacts, such as online recommendation systems (Wang and Benbasat 2008). Relating to PPM, Bansal et al. (2005) proposed trust as an influencing factor for service-switching. Recently, Lai et al. (2012) introduced trust in a PPM construct to explain switching behavior in mobile shopping. If users' trust in a SECO or in its components decreases, they will consider switching to another SECO to which they attribute a higher level of trust. Thus, we consider low trust to be a push factor and predict that it will have a positive influence on intention to switch. Subsequently, we hypothesize:

\[ H_{1c}: \text{Low trust in a SECO positively influences the push factor.} \]

High price perception: Price-related issues are an integral part of migration theories, and there is also support for its integration into service-switching. Consumers are more likely to switch if they perceive their current service providers' prices to be high (Bansal et al. 2005). Concerning the application of PPM, price has only been considered by Bansal et al. (2005). Price perception of the SECO is mainly influenced by the purchase of the end-user device and the expenditures on apps and in-app purchases (Forbes 2013). Since these are integral parts of the SECO, high price perception presumably has a positive influence on the intention to switch SECOs, and we hold:

\[ H_{1d}: \text{Perception of high SECO price positively influences the push factor.} \]
**Pull Factors**

Pull factors are “positive factors drawing prospective migrants to the destination” (Moon 1995). In the context of SECOs, users can either be attracted to another SECO as a whole or to certain components such as the smartphone. This attraction forms users’ desire to switch to a different SECO.

*Attractiveness of alternatives:* Bansal et al. (2005) postulated that the attractiveness of alternatives is “the only existing variable from the service-switching literature that conforms to this conceptualization” of a pull factor. Following this notion, Jones et al. (2000) defined the attractiveness of alternatives as “customer perceptions regarding the extent to which viable competing alternatives are available in the marketplace.” Concerning the availability of alternatives, Jones et al. (2000) showed that a few viable options decrease users’ defection levels, while further research identified that perceived higher attractiveness of alternatives is positively related to the intention to switch to one of the alternatives (Kim et al. 2006; Zhang et al. 2012; Zhang et al. 2008). Besides the inclusion of attractiveness of alternatives in various IS publications (e.g., Kim et al. 2006), this factor has been considered in several PPM constructs as a pull factor (Chang et al. 2014; Hou et al. 2009; Ye and Potter 2011; Zhang et al. 2012). In addition to the evaluation of the overall perceived attractiveness, users also assign different attraction levels to different components of a SECO, such as the smartphone or the app store and apps. Therefore, if users assign higher benefits to different components of an alternative SECO, the intention to switch to a more attractive ecosystem is raised. Thus, we posit:

**H2:** Attractiveness of alternatives positively influences users’ intention to switch.

**Mooring Factors**

Migration in any context is a complex and difficult decision. Thus, the consideration of solely push and pull factors fails to represent the entire migration decision. Instead, it is also necessary to consider mooring effects in the decision process (Boyle et al. 1988). Mooring factors are understood as intervening factors that constrain users’ migration decisions, despite the presence of strong push and pull factors.

*Subjective norm:* Migration theorists propose the inclusion of subjective norm to understand migration decisions, since the engagement with or the pressure of the social environment exerts a high influence (Bansal et al. 2005). Ajzen and Fishbein (1980) defined subjective norm as perceptions of social pressures placed on individuals to engage in a certain behavior. In the service-switching literature, the direct influence of subjective norm on consumers’ attitude towards switching behavior and switching intentions is highlighted (Bansal and Taylor 1999; Bansal et al. 2005). IS research has also found significant effects of subjective norm in the context of the adoption and usage of technologies (Taylor and Todd 1995; Venkatesh and Davis 2000). Ye and Potter (2011) examined web browser switching intentions while integrating subjective norm into the PPM framework. In certain cases users, are virtually ‘forced’ to comply with the usage behavior of their environment if they wish to participate in social interactions with their peer group (e.g., for messaging services). Hence, subjective norm can have substantial influence on the intention to switch SECOs and may even prevent users from switching. Thus, subjective norm is considered as a mooring factor, and we hypothesize:

**H3a:** Subjective norm positively influences the mooring factor.

*Switching costs:* Marketing and IS researchers often follow the broad definition of switching costs as “perceived economic and psychological costs associated with changing from one alternative to another” (Jones et al. 2002). Although some authors further distinguish between switching cost types, Ray et al. (2012) state that “no generalizable collection of switching-cost factors has been identified that is customized for IS research or that can be applied across IT settings.” We follow this line of argumentation, also for the sake of questionnaire brevity. Considering operationalization within the PPM framework, switching costs is mostly implemented as a mooring factor (Bansal et al. 2005). Switching costs is either implemented as sole mooring factor (Chang et al. 2014; Zengyan et al. 2009; Zhang et al. 2012; Zhang et al. 2008) or is combined with other aspects such as subjective norm (Bhattacharjee and Park 2014; Hou et al. 2009; Ye and Potter 2011). The nature of SECOs also suggests implementation as a mooring factor. Consumers who once decided to use and invest in a certain SECO presumably face strong switching costs. They will for instance consider the efforts to transfer data from proprietary apps (e.g., contacts) or from other third party applications. There is further empirical evidence that switching costs have a negative
influence on switching intention (Bhattacherjee and Park 2014). Thus:

**H3b: Switching costs positively influence the mooring factor.**

**Habit:** Habit is defined as “learned sequences of acts that have become automatic responses to specific cues, and are functional in obtaining certain goals or end states” (Verplanken and Aarts 1999). For instance, a daily commute via subway can be understood as a cue in the environment. Based on this understanding, habits are formed when actions are performed regularly in a familiar environment. In IS, habit has also been defined as “the extent to which people tend to perform behaviors (use IS) automatically because of learning” (Limayem et al. 2007). Several studies have examined habit’s role in IS usage, postulating a positive influence on continued usage of a system (Gefen et al. 2003; Kim and Malhotra 2005; Limayem et al. 2007; Venkatesh et al. 2012). Murray and Haeubl (2007) examined the formation of “skilled-based habits of use,” such as learning the navigation of a specific Internet homepage. Polites and Karahanna (2012) identified the significant effect of “incumbent system habit” as an antecedent of inertia in order to explain further intentions to use a system. Ye and Potter (2011) conceptualize habit as a mooring factor in the PPM framework. Although habit is formed via repeated executions and becomes an automatic response, it also becomes increasingly important in the rapidly changing environment of consumer technology (Venkatesh et al. 2012). In SECOs, consumers deliberately use, consume, and change components of an ecosystem. Especially the habituation to the OS and the haptic factor of end-user devices presumably contribute to the formation of habit. Thus, habit is considered a mooring factor, and we hypothesize:

**H3c: Habit positively influences the mooring factor.**

Mooring variables not only directly affect intention to switch, they can also moderate the relationship between push and pull factors and users’ intentions to migrate (Lee 1966). Thus, it is expected that even if push and pull factors have strong direct effects, mooring variables can reduce the direct influence up to a point where users might even remain with the incumbent system (Bansal et al. 2005). We postulate moderating effects of the mooring factors on both the pull and on the push constructs. Owing to low satisfaction, low quality, low trust, and high price perception, users are driven away from their current SECO. Each of these factors is likely to be influenced by the three mooring factors subjective norm, switching costs, and habit. For instance, users may lose trust in a SECO provider and will have a higher intention to switch. However, users might remain with their current SECO if for instance they value potential risks related to trust less than the effort of switching to another SECO. Likewise, users’ intentions to switch, as described by the pull factor attractiveness of alternatives, is likely to be influenced by the mooring factors. Therefore, an alternative SECO only appears attractive to consumers if the mooring effects do not exceed certain values, otherwise users might not even consider switching to other SECOs. Thus, we postulate:

**H4a: The mooring factor moderates the influence of attractiveness of alternatives on intention to switch. The stronger the mooring effect is, the weaker the relationship between push factor and intention to switch will be.**

**H4b: The mooring factor moderates the influence of attractiveness of alternatives on intention to switch. The stronger the mooring effect is, the weaker the relationship between pull factor and intention to switch will be.**

**Operationalization and Survey Instruments**

In line with previous research, the PPM framework is modeled as formative constructs at the levels of push and mooring (Ye and Potter 2011). The first-order constructs that form the aggregated PPM constructs are also modeled formatively. This is in line with methodological guidance that suggests the modeling of formative constructs if the construct is a combination of the indicators (Fornell and Bookstein 1982) or if indicators cause the constructs (Rossiter 2002). The first-order constructs in the different PPM constructs, namely low satisfaction (Oliver and Swan 1989), low quality (Taylor and Baker 1994), low trust (Gefen et al. 2003), subjective norm (Taylor and Todd 1995), switching costs (Burnham et al. 2003), and habit (Limayem et al. 2007) are all modeled as reflective items, which is in line with the implementations of the aforementioned authors. Only high price perception is not clearly indicated as either formative or reflective by (Bansal et al. 2005). We decided to use a reflective construct, since the items are mutually interchangeable (Jarvis et al. 2003). Also in line with previous research, we decided to
include all pull aspects in one common factor “attractiveness of alternatives” (Bansal et al. 2005), the items of which were also modeled as reflective.

While there have been multiple applications of the PPM framework, the connection between the single PPM subconstructs (e.g., low satisfaction) and the five different SECO components (e.g., smartphone and operating system) has not yet been established. We implemented the different components as formative single-item factors. To connect these to the PPM framework, we adopt the formative-formative type model, which is used when “the lower-order constructs are formatively measured constructs that form a more abstract general concept” (Becker et al. 2012). Transferring this approach to mobile OS ecosystems, the five ecosystem components (items) formatively form the construct of the PPM first-order factors (such as high price perception and others), which also load formatively on the single PPM constructs. Owing to the large number of second-level factors in the PPM framework, an extension that adds another layer to account for the S ecosystem components constituted a challenge in terms of questionnaire length. In this regard, our implementation of the different ecosystem components as formative single items that form the second-level PPM factor constitutes the most compact operationalization.

Since our focus here is to explain end-user switching intentions, only data from participants who own a personal smartphone were considered. To provide a comprehensive model, it was of great importance to us to cope with participants with different switching experiences. Mainly, there are two groups: Users, who have already switched from their SECO (switchers) and those, who have yet not switched their SECO (non-switchers). Thus, we adapted the PPM framework’s items to the participants’ experience, i.e., switchers were presented with retrospective questions, i.e., users had to answer questions while recalling the reasons of switching from the prior to the current mobile OS ecosystem. In contrast, questions for non-switchers addressed a possible change from the current to an alternative ecosystem. Although the two groups had to think of different situations, we could use the same PPM items, and only had to apply slightly different wordings.

For the measurement constructs we used multi-item, pre-validated scales. We made minor modifications so as to achieve a better fit with the context of mobile OS ecosystems. All constructs were measured by 7-point Likert scales (ranging from 1 = lowest to 7 = highest). All original items were first adapted to the context of mobile OS ecosystems and were then translated into German.

Results

Data Acquisition and Descriptive Statistics

We carefully pretested the visual design and the structure of the questionnaire to ensure the reliability of the constructs and the comprehensibility of the questions. Pretest participants included researchers as well as students. All members owned a smartphone, but not all of were familiar with the concept of SECOs. Based on their feedback, we made minor changes to the wording for the sake of better comprehensibility. To ensure a shared understanding of the SECO concept, we produced a video explaining the concept of ecosystems and showed it prior to the questionnaire.

We distributed the online questionnaire via campus mailing lists and social media homepages, both for private and professional use, and 705 respondents completed the questionnaire. To obtain a robust data sample, we removed participants without a private smartphone. Furthermore, we removed 19 users owing to extremely low completion times. Following Hair et al. (2014), we also removed observations if a dataset contained more than 15% missing values. Subsequently, the data comprised 501 observations, 270 (54%) from female respondents and 231 (46%) from male ones. Although most of the participants were college students (56%), there was also a large proportion of employees (32%) and a smaller sample of self-employed participants (5%) and of high school students (3%). Participants reported an average usage time of their current mobile OS ecosystem of 1.5 years. Of 501 responses, 129 (26%) were switchers and 372 (74%) non-switchers. Participants stayed about three years (21.7 months) with their prior ecosystem before moving to their current one.

Measurement Model

We applied PLS analysis using SmartPLS 3.0 to evaluate the research model and to test the hypotheses (Ringle et al. 2014). PLS can handle complex structural models and can access formative as well as
Extending Switching Theories from Products to Ecosystems

When running PLS (1,000 iterations, 1*10^-5 stop criterion), the model achieved stability within two completed iterations. For missing values, all missing data points were replaced with the mean value of the remaining data points of the item (Ringle et al. 2014). We conducted Harmon’s single-factor test to assess potential common method bias, but found no evidence for common method bias.

We analyzed the reflective items of our measurement model using recommended validation procedures (Chin 2010). We pooled and factor-analyzed scale items in one domain to assess their convergent and discriminant validity (Table 1). While convergent validity was determined both at the individual item level and at the specified construct level, discriminant validity was assessed by analyzing the average variance extracted (AVE). All constructs met the suggested threshold value for the AVE (> .50). We assessed construct reliability by computing the composite reliability for each construct. All constructs had a composite reliability above the suggested threshold value of .70 (Bagozzi and Yi 1988).

The push and the mooring higher-order constructs were modeled formatively. To form the higher-order constructs, all respective items of the related constructs were loaded into the higher-order constructs. For instance, the items of push first-order factors low quality, low satisfaction, low trust, and high price perception were reflectively loaded, such that the assessment of outer loadings can be transferred to the higher-order constructs. Attractiveness of alternatives resembled the pull factors as a reflective construct. Based on the outlined description, the push, pull, and mooring constructs established convergent validity. Further, multicollinearity did not appear to be an issue, since all factors had VIFs of less than the recommended threshold of 3.5. As a result, the constructs as well as the research model as a whole were regarded as valid and reliable.

### Table 1. Overview of Reflective Items

<table>
<thead>
<tr>
<th>Constructs</th>
<th>Cronb. alpha</th>
<th>CR</th>
<th>AVE</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
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<tbody>
<tr>
<td>Low satisfaction (1)</td>
<td>.956</td>
<td>.966</td>
<td>.852</td>
<td>.923</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Low quality (2)</td>
<td>.891</td>
<td>.932</td>
<td>.821</td>
<td>.805</td>
<td>.906</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>Low trust (3)</td>
<td>.827</td>
<td>.885</td>
<td>.657</td>
<td>.482</td>
<td>.429</td>
<td>.811</td>
<td></td>
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<td>High price perc. (4)</td>
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<td>.871</td>
<td>.772</td>
<td>.132</td>
<td>.097</td>
<td>.039</td>
<td>.879</td>
<td></td>
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<td>Subj. norm (5)</td>
<td>.904</td>
<td>.954</td>
<td>.912</td>
<td>-.129</td>
<td>-.180</td>
<td>-.097</td>
<td>-.120</td>
<td>.955</td>
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<td>Switching costs (6)</td>
<td>.884</td>
<td>.920</td>
<td>.742</td>
<td>-.466</td>
<td>-.492</td>
<td>-.205</td>
<td>-.152</td>
<td>.227</td>
<td>.861</td>
<td></td>
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<td>Habit (7)</td>
<td>.837</td>
<td>.903</td>
<td>.758</td>
<td>-.481</td>
<td>-.434</td>
<td>-.280</td>
<td>-.015</td>
<td>.041</td>
<td>.390</td>
<td>.870</td>
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<td>Attract. of altern. (8)</td>
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<td>.901</td>
<td>.753</td>
<td>.646</td>
<td>.609</td>
<td>.365</td>
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**Test of Structural Model and Hypotheses**

For each of the different first-order constructs, we analyzed all SECO components (modeled as single items) concerning convergent validity (Hair et al. 2011 suggest a threshold of .7) and their outer loadings. For the latter, values between .4 and .7 are recommended, and an item within these boundaries should only be removed if a CR increase is evident (Hair et al. 2014). Accordingly, for most of the higher-order constructs, we dropped certain mobile OS ecosystem components. Figure 2 presents an overview of the results, while colored components were statistically significant at the .05 level (detailed outer loadings are presented in the Appendix). Subsequently, we will present the results for each of the push, pull, and mooring constructs and their subconstructs.

Together, the push, pull, and mooring effects in the research model explained 64.6% of the variance of the users’ intention to switch. Concerning the effect sizes of the push, pull, and mooring constructs on intention to switch, the push construct showed a small effect size (f^2 = .025), while pull (f^2 = .252), and mooring constructs (f^2 = .165) are considered to have medium effects on the endogenous variable. The Stone and Geisser Q^2 test was performed, and Q^2 values of all constructs were greater than 0, indicating...
support of predictive relevance for the endogenous variable intention to switch.

We further conducted a subgroup analysis to test for potential differences between participants, who have already switched their smartphone SECO (switchers) and those who have not (non-switchers). Our tests revealed no significant differences between these two groups, indicating that the model is applicable for both user types.

**Push Factors**

The push construct was significant at the 1% level, with a path coefficient of .146 on the endogenous variable intention to switch. In the push construct, low satisfaction displayed the highest path coefficient of .576 (p < .01); H1a was therefore supported. At the component level, especially low satisfaction with the OS as well as app store and apps fueled low satisfaction.

The relationship between low quality and the push construct displayed a high path coefficient (.336) and was significant at the 1% level. Therefore, H1b was supported, as low quality positively affects the push factor. Similar to low satisfaction, at the component level the OS, app store and apps, and interface with other devices were significant. Assessing the path strength of low trust, a fairly strong effect was observed (.220; p < .01). As hypothesized, users assigned a high value to the factor trust in digital products and services; thus, hypothesis H1c was supported. Trust played a significant role concerning the operating
system, app store and apps, and interface with other devices. With a path coefficient of .019, high price perception did not have a significant influence on the push construct (p = .132). Participants were apparently not influenced by the overall price perception of the ecosystem; thus, hypothesis H1d was not supported.

**Pull Factors**

Attractiveness of alternatives resembles all pull factors, had a path coefficient of .431, and achieved significance at the 1% level. Compared to the push construct, it seemed that users’ switching intentions depended more on attractive alternatives rather than the shortcomings of their current SECO; thus, Hypothesis 2 was supported. Therein, the OS was considered as the most decisive factor, as assumed before. In addition, smartphone, app store and apps, and interface with other devices also exhibited significance at the .05 level.

**Mooring Factors**

Mooring had a negative and statistically significant influence (-.317, p < .01) on intention to switch. Compared to the push and the pull factors, mooring had the second-largest influence on intention to switch, underlining its high overall importance.

Subjective norm exhibited a comparably small (.136) but still significant impact on the mooring construct (p < .01); thus, hypothesis H3a was supported. Thus, even if users have identified an attractive alternative SECO, it could be the case that they do not switch because trusted individuals suggested that they stay with their current ecosystem. Interestingly, smartphone was the only component that had a significant impact on subjective norm. The relationship between switching costs and the mooring construct had the highest path coefficient of all mooring factors (.738, p < .01), and we found support for H3b. Considering mobile OS ecosystems, this implies that users avoid investing time, money, and further effort into understanding a different SECO. At a component level, all components have significant impacts on switching costs. Habit also had a strong influence on the mooring construct (.397, p < .01), which provided support for H3c. As hypothesized, consumers who repeatedly use a technology are less likely to switch. Since many users interact with their mobile OS ecosystem very often, automatic behaviors are likely to form easily. Significance of all components indicates that habit was related to all parts of the mobile OS ecosystem.

Besides the direct influences on intention to switch, it is also of interest whether mooring factors moderate the push and the pull factors. We found no significant moderating influence on the push construct (.007, p = .661); thus, hypothesis H4a was not supported. Smartphone users are therefore not influenced by mooring factors when they are pushed away, i.e., they have already formed a wish to leave their current SECO and stick to this intention independent of the extent of the mooring factors. In contrast, a different picture emerged for the attractiveness of alternatives, which was negatively moderated by the mooring construct (-.043, p < .01); thus, hypothesis H4b was supported. Hence, users can be withheld from switching to an attractive alternative owing to strong mooring effects that decrease the pull factors’ effects. Table 2 presents an overview of the different path coefficients and the hypothesis test results.

**Discussion**

The analysis of the results has shown that the influences of the individual mobile OS ecosystem components differ substantially across the different first-order constructs – even between different push or mooring constructs. Further, even the impact of the smartphone as presumably the most expensive and most tangible component of the ecosystem differs substantially and does not have a significant influence on all constructs. Thus, for a fine-grained analysis, it is not sufficient to simply take smartphones as a proxy for the ecosystem as a whole.

Comparing the influences of the push, pull, and mooring factors, it is remarkable that the push construct exhibits the weakest influence on intention to switch. This implies that the switching decision is not triggered primarily by factors of disappointment with the status quo, which push consumers away from their current ecosystem, but rather by the attractiveness of alternatives and the extent of mooring.
constraints. In the push construct, low satisfaction is the main driver. Moreover, in any case, low quality of the overall ecosystem plays a decisive role. Considering the ecosystem component level, the OS and the installed apps mainly influence perceptions of low satisfaction and of low quality. Here, users seem to expect flawless performance and extensive functionality. Thus, users are pushed away from their current SECO if these core parts of the ecosystem do not meet their expectations. Besides satisfaction and quality, trust is the third influencing construct. This result is in line with prior IS research, which confirms that trust plays a key role in selling digital products and services to consumers. Especially trust in the OS is of high relevance. Since consumers store an increasing amount of private information on their smartphones, they expect their data to be safe and to be handled with care.

One of the most revealing aspects is the non-significance of high price perception. It appears that users do not perceive high prices as a substantial factor at the overall level of the mobile OS ecosystem. Instead, users primarily perceive the price of the smartphone to be the most relevant aspect. In contrast, the prices of accessories, and the software-related components (OS, app store, and apps) of the ecosystem are not considered. While presumably not all SECO users invest in accessories, as an explanation for the latter, the much-discussed free mentality of a large share of the apps and the mobile OS seem to lower perceptions of high prices. For instance, mobile OS updates can be downloaded at no additional costs and 90% of all app store downloads are gratis (Engadget 2013). In addition, consumers may not remember small expenses such as in-app purchases. In contrast, the smartphone is usually the most expensive single component of the ecosystem. Thus, it is comprehensible that users value smartphones as the most influential aspect in the high price perception.

Attractiveness of alternatives is the strongest driver on intention to switch, and exerts a much stronger effect than the push construct. This finding is congruent with results from previous migration studies in marketing (Bansal et al. 2005) and IS research (Hou et al. 2009). Concerning the ecosystem components, participants assigned the highest value to the attractiveness of alternative OSs, followed by smartphones, app store, and apps. In conjunction with the strong influence of perceived low quality, it can be implied that users are more likely to consider a switch to another mobile OS ecosystem if a potential alternative offers a well-performing OS.

The mooring effects have the second-strongest impact on intention to switch. In line with previous research, we found that users are more likely to switch if switching costs are low. The comparably strong influence of switching costs on intention to switch also supports prior findings from other PPM studies (Bansal et al. 2005; Bhattacharjee and Park 2014; Chang et al. 2014; Hou et al. 2009). At the component level, users mostly fear high switching costs related to the OS. This is for instance relevant for the transfer of calendar and contact data from one OS to another. In addition, users are more likely to switch if no substantial habitual behavior has been formed with the current ecosystem. When habit is strong,
intention to switch is substantially weakened, which is in accordance with the findings of Ye and Potter (2011). We found that mainly the components OS, smartphone and apps are relevant for the perception of habit. When considering that users interact on average more than two hours per day with their mobile OS ecosystem, it is likely that habitual behavior related to usage (OS, apps) and haptic aspects (smartphone) can be formed quickly. Further, it is notable that the significant influence of the social environment (e.g., family or friends) is only relevant for smartphones.

One advantage of the PPM framework is the possibility to consider moderating factors, particularly relating to the influence of mooring factors on the push and pull factors. Our results reveal that mooring effects have no significant influence on the push constructs. This implies that once users are pushed away from their current ecosystem, high mooring effects will not hold them back from migrating to another smartphone SECO. On the contrary, mooring effects significantly reduce the pull effect of an attractive alternative. This means that although smartphone users may be attracted to another SECO, mooring factors such as high switching costs or their friends’ opinions can prevent them from actually switching.

As anticipated, based on the interviews we conducted and the analysis of our research model, there were no significant differences observed between switchers and non-switchers. Thus, experiencing a switch from one SECO to another does not substantially alter users’ criteria for conducting another switch. This also implies that the overall research model is suitable to explain mobile OS ecosystem switching for both groups.

**Theoretical Contributions**

Despite the popularity of SECOs, very little is known about users’ decisions related to SECO adoption and switching behaviors. While previous research has taken a first step in this direction, it has not accounted for the full complexity of SECOs, and has used a proxy in lieu of the individual ecosystem components. With the development of our empirical research model, we sought to deepen understanding of switching behavior concerning mobile OS ecosystems. To our best knowledge, our study is one of the first to go beyond a simplified or very abstract representation of SECOs and that explicitly accounts for different ecosystem components. Our extended PPM research model amplifies research on IS post-adoption and switching behaviors. It explains 64.6% of the variance of users’ switching intentions concerning mobile OS ecosystems and thus builds a strong basis for future research on ecosystem switching. Even for more complex ecosystems, the methodology we developed allows for appropriate questionnaire length.

In accordance with prior research, we show that the attractiveness of an alternative mobile OS ecosystem dominates migration in comparison to factors that push users away from their current ecosystem. Mooring factors are the second-strongest influence, while significantly moderating the pull effect. In turn, this affirms the recent efforts by IS researchers to place a stronger focus on related concepts such as habit. Moreover, at a component level, our model illustrates the importance of individual SECO components (especially OS, smartphone, and apps) for switching intentions.

Our research has shown that the theoretical lens of the PPM framework is an effective tool to analyze SECOs, which not only reflects the negative factors of the current usage state and the positive factors of the alternatives, but also includes situational and contextual constraints. In accordance with previous works, our research advances the application and understanding of the PPM framework in a novel context with high practical relevance. Assuming a steadily increasing diffusion of connected and interdependent technologies, in our view, our approach paves the way for future research on such complex systems.

**Practical Implications**

The consumer electronics market, particularly the smartphone segment is a highly competitive environment. While Android and Apple currently dominate the market, other players (such as Windows mobile or Firefox) are seeking to increase their market shares. Thus, why end-users switch their ecosystem is of great interest for mobile OS ecosystem providers. Based on our results, one can draw further implications and recommendations for ecosystem providers. First, we were able to show that, owing to the dominance of the push construct, ecosystem providers are well advised to proactively communicate the advantages and functionalities of their ecosystem so as to attract consumers. Here, providers must understand the role of attractiveness of alternatives in the switching process. Users often identify one specific attractive component (based on our data, this was the mainly the OS) rather than
forming an overarching attractiveness for a different ecosystem. Hence, providers should create opportunities for users to easily, and without cost, experience the crucial aspects of their ecosystems SECO.

Second, our results have also demonstrated that mooring factors are able to keep users from switching. Therefore, ecosystem providers, especially those with lower market shares, should facilitate switching processes. For instance, providers could offer tools that help users to transfer data from the incumbent mobile OS. In addition to switching costs, habit plays a key role. To prevent users from switching to another ecosystem, providers should take actions to facilitate habitual behavior. Therefore, providers should design new products that take advantage of existing user habits rather than trying to change users' habits.

Finally, mobile OS ecosystem providers should carefully examine possible dominant sources of users’ dissatisfaction to increase customer retention rates. This mainly relates to their software’s freedom from errors and the justification of users’ trust.

Conclusion

Our study sought to explain users’ switching intentions for SECOs and to distinguish the impacts of the different ecosystem components. While previous research used abstract representations or smartphones as a specific ecosystem component as a proxy for the entire SECO, in our view, it is necessary to break down the different determinants on a component level to account for SECO complexity and the substantial value created by the components. We extended the PPM framework and presented a comprehensive model that accounts for the individual ecosystem components, while maintaining questionnaire brevity.

Our results indicate that especially pull factors have strong positive influences on switching intentions, while push and mooring factors exhibit a comparably weaker, but statistically significant influence on intention to switch. While these implications are similar to previous research, our results show that there are substantial differences in impact across the ecosystem components that appear across all subconstructs of the PPM framework. Therefore, using a single ecosystem component as a proxy for the entire SECO might lead to wrong implications both for research and practice. For instance, smartphones exhibit almost no influence on push factors, while exhibiting significant influences on all mooring and pull factors.

For future research on other SECOs, we therefore strongly suggest an individual assessment of how users perceive a specific SECO and which components are the most relevant to them. The results from our interviews confirmed a large gap between researchers’ and users’ understandings of certain concepts and terms. Thus, it is critical to have a profound understanding of users’ perceptions of a SECO. Based on a deep understanding of user behaviors, researchers need to decide which SECO components they will implement in their research model and whether certain proxies are in fact appropriate. Implementing proxies that do not fully cover the entire complexity can bias the results. We provided a methodological approach that balances questionnaire lengths and offers a high level of detail. Future research should further seek to develop methods to handle large systems complexity and dependencies between system components, since these are likely to become more prevalent in times of embedded systems and universal connectivity.

The study has limitations. First, despite obtaining a large sample of 501 participants, our sample is characterized by a proportionally high number of students. Targeting student audiences was suitable for our research, since students resemble a key smartphone user group and thus presumably need lower effort to imagine the given context. However, further studies should seek to validate our results with a representative participant sample to assess cultural and economic influence factors. Second, similar to other survey studies, self-reported usage data might be subject to certain biases, such as the social desirability of specific answers. Third, although mobile OS ecosystems have become almost omnipresent and are often used in research, other SECO types might have specific characteristics that could impact on the results. Future research should therefore replicate our analysis in different scenarios.
References


Extending Switching Theories from Products to Ecosystems


Extending Switching Theories from Products to Ecosystems

### Table 3. Overview of Formative Items

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