IT-Enabled Personalization Outcomes in Hospitality.

1. Introduction

Information technology plays an important role in tourism industry, as it facilitates travelers' trip planning activities (MacKay and Vogt 2012) and helps tourism industry to create value (Cabiddu et al. 2013). An essential goal of the information system (IS) discipline is to understand the full complement of consequences stemming from the introduction of information technology in organizations (Hevner et al. 2004; Silver and Markus 2013). In this effort, IS scholars develop conceptual frameworks that capture the structure of IS artifacts and their interactions with the real-world so as to facilitate system design, building and maintenance (Wand and Weber 2002; Weber 2012). Representation theory (Wand and Weber 1995) is one such effort focused on explaining how an information system conveys information and meanings to represent the real world. Originally conceptualized over three decades ago, representation theory has recently seen a resurgence of interest. However, despite being a native IS theory it has been surprisingly underutilized to explain the use of IT in their social context (Burton-Jones and Grange 2013).

Our work focuses on IT-enabled service personalization in the context of hospitality industry. Despite the growing interest in service science, little empirical research to date investigated the use of IT in service personalization and delivery fulfillment (Hwang and Seo 2016; Xu et al. 2014). IT-enabled Customer Service Systems (CSS) are the collection of information systems that mediate and enable the performance of customer services to increase overall customer value by improving the utility realized by customers using the service system (Piccoli et al. 2004). That is, if effectively used, an IT-enabled CSS fosters efficiency and effectiveness in service delivery

(Bonfield 1996) and may serve as an example of 'computer-mediated travel counselor' (Hruschka and Mazannec 1990).

In this study, we contribute to the development of representation theory and its application to understanding effective system use. Specifically, we measure the effect of faithful representation and users' informed action on system performance in terms of enhanced preference elicitation and improved customer service rating. To our knowledge ours is the first empirical test of these relationships in a field study using a live system in organizations, rather than a laboratory setting. Our contribution encompasses both theory extension and intension (Burton-Jones et al. 2017). First, by applying representation theory to the IT-enabled service personalization context (i.e., extension), we contribute to the literature by showing how faithful representations provided by IT-enabled CSS improve the preference elicitation process. Second, with representation theory as theoretical lenses, we adopt the model of system effective use to explain the effect of informed action on system performance. More specifically, our paper provides a new measure of informed action (i.e., intension) – one of the dimensions of effective system use (Burton-Jones and Grange 2013).

The paper begins by first providing a review on representation theory and system effective use to develop the research hypotheses. We then describe the context of the study and discuss the three elements of the IT-enabled CSS for service personalization (physical structure, surface structure and deep structure) to provide an overview of the information system studied. Finally, we present the data analysis results to evaluate the effect of IT-enabled CSS and we discuss the implications of our findings.

2. Literature Review

Representation Theory

Representation theory hinges on the basic premises that humans devise information systems because individuals and organizations need information to survive and thrive. Thus, they design and develop information systems to understand and represent the world (Wand and Weber 1995; Weber and others 1997). In this view, *representation* is the essence of an information system. That is, information systems are designed and built to "track states of and state changes in other systems. By observing the behavior of an information system, we obviate the need to observe the behavior of the system it represents" (Weber 2003, p. viii). Using information systems yields advantages in terms of efficiency when observing physical systems and in terms of feasibility when representing conceived systems (i.e., simulations of systems that have yet to be built in the physical world).

So defined, information systems have three elements: physical structure, surface structure and deep structure (Wand and Weber 1995). Physical structure elements comprise the technology used to implement the system, which include "the machinery that supports the other structures" (Burton-Jones and Grange 2013, p. 636). This is the realm of hardware. Surface structure elements embody the way the system appears to, and interacts with, users. This is the realm of user interfaces. Deep structure elements "represent stakeholder perceptions of the meaning of the focal real-world phenomena (e.g., data objects and business rules embedded in program code)" (Burton-Jones et al. 2017, p. 3). The emphasis on deep structure is the defining feature of representation theory. More specifically, while physical and surface structures are a means for accessing the deep structure, the latter encapsulates the primary purpose of an information system. Namely, to provide faithful representations of the phenomenon of interest. It is, in fact, the degree of faithfulness of these representations to the states of the real-world system being tracked, initially and over time, that determines the 'goodness' (i.e., quality) of the information system (Wand and Weber 1995). As individuals and organizations build and use information systems to enable decision making and action, higher degrees of faithful representation of the domain of interest provide a superior basis for such action by giving access to more accurate information (Burton-Jones and Grange 2013).

Effective Use

As originally conceived, representation theory adopted a narrow definition of information system, focusing on an "internal view" predicated on the assumption that "an information system is an object that can be studied in its own right – independently of the way it is developed and deployed in its organizational and social context" (Wand and Weber 1995, p. 205). However, the theory has recently been extended, in the specific domain of effective system use, to "studying IS artifacts in use in their social context" (Burton-Jones and Grange 2013, p. 639). The usage of IS artifacts is defined as "a user's employment of a system to perform a task" (Burton-Jones and Gallivan 2007, p. 659), which simultaneously encompasses user, system, and task (Burton-Jones and Straub Jr 2006). Effective use, broadly defined as "using a system in a way that helps attain the goals for using the system" (Burton-Jones and Grange 2013, p. 633), is the core objective of a systems' introduction because it is not technology per se that yields the expected benefits, but rather its (effective) utilization (Orlikowski 2000). This extension of representation theory advances three dimensions of effective use (Burton-Jones and Grange 2013):

- Transparent interaction: the extent to which users seamlessly access the system's representations unconstrained by its surface and physical structures.
- Faithful representation: the extent to which users do access representations from the system, reflecting the domain being represented.

- Informed action: the extent to which users act upon the faithful representations they obtain from the system to improve their state.

A defining feature of this framework is the fact that the three dimensions provide an assessment of system use – not of the system or the users taken individually. In other words, whether a representation is faithful or not, does not depend uniquely on the characteristic of the system, nor the competencies of a user, but rather on the interaction of the users, the system and the task being completed. It follows that there will be variations of outcomes for different people using the same system (DeSanctis and Poole 1994) as well as usage patterns clustering around a central tendency of predicable uses (Markus 2005) characterized by varying degrees of effectiveness.

The three dimensions of effective use are hierarchically related such that a user must be able to access the representations housed in the system (transparent interaction). Interaction with the information system must be intelligible to the users so that they can extract meaning from the system (faithful representation). Finally, access to faithful representations must enable individuals, or organizations, to engage in activities that result in improved performance (informed action). In short, "transparent interaction activates the informating potential of an IS, representational fidelity ensures that this potential is positive, and informed action leverages it" (Burton-Jones and Grange 2013, p. 644).

IT-enabled service personalization

Our focus in this study is the relationship between effective use and performance in the context of service personalization. Service personalization is the process of using individuals' own information to tailor the service and the transactional environment to improve the benefits accruing to them (Lee and Cranage 2011; Shen and Ball 2009). Thus, service personalization let the service providers to utilize individuals' preferences as a factor co-creating value (Cabiddu et al. 2013, Prebensen et al. 2013). Generally speaking, service personalization includes two subprocesses: learning and matching (Murthi and Sarkar 2003). The former is a preference elicitation and gathering phase whereby an organization collects specific customer preferences through the interaction between the service provider and the service consumer (Glushko and Nomorosa 2013). The latter consists of matching customer preferences to specific offerings, or in customizing the offering to accommodate the learned preferences (Adomavicius and Tuzhilin 2005). In the case of service personalization, matching consists of modifying certain components of the service offering, including service delivery, service products and service environments, based on the learned consumer preferences.

While the service personalization process may or may not be IT-enabled, information systems are increasingly at the core of service personalization and delivery (Cenfetelli et al. 2008; Melián-González and Bulchand-Gidumal 2016; Piccoli and Lui 2014). The growing literature on IT-enabled CSS shows that customer service is one of the functions that has been deeply impacted by the advent of Information Technology, and such impact will likely intensify rather than subdue in the future (Etzion and Pang 2014; Scherer et al. 2015). The increasing deployment of CSS enables firms to provide high quality and personalized service at a reasonable cost (Neuhofer et al. 2015; Xu et al. 2014).

3. Hypotheses Development

Preference elicitation and faithful representation

Representation theory posits that people rely on information systems to obtain representations that aid them in cognitively understanding a real-world domain and enables them to better function in such domain. The recent research on effective use adds that individuals (or organizations) need to act upon the representations produced by information systems to attain their goals (Burton-Jones and Grange 2013). In the context of service personalization, the objective of preference elicitation during the learning phase is to surface as complete as possible a set of the customers' preferences for the product or service (Murthi and Sarkar 2003). Both the customer and the firm share this goal of complete and precise preference elicitation and organizations design and develop IT-enabled CSS to aid in the elicitation process (Komiak and Benbasat 2006; Piccoli et al. 2017). However, there are two limiting factors. First, the firm can only provide the set of personalization options that it can feasibly deliver. For example, while a guest may value broadband internet access in her room, a hotel can only offer such service if it has contracted with a broadband ISP and it has installed the appropriate networking infrastructure. Second, the customer can only express preferences if they cognitively understand the domain (i.e., what options are available and how they map to their expectation of a high-quality customer experience). Individuals generally hold well-differentiated values only for the most basic attitudes and frequently encountered experiences (Fischhoff 1991). That is, many individual preferences are ill-defined and are constructed on the spot in response to task demands (Bettman et al. 1998; Gretzel and Fesenmaier 2005). Thus, in the service context, people generally do not have clear preferences unless they are facing familiar products or service options (Coupey et al. 1998). Rather, they formulate their attitudes and requests when they are asked to express them (Slovic 1995). Previous research shows that decision aids, such as a taxonomy or framework linking product features and individual evaluation criteria (West et al. 1996), or categories of available options (Mogilner et al. 2008), enhance individuals' understanding of their own preferences and satisfaction with their choices. These decision aids and categorizations are examples of deep structures introduced to "manifest the meaning of the real-world system the information system is intended to model" (Wand and Weber 1995, p. 206). More generally, we posit that IT-enabled CSS designed to increase the degree of faithful representation of the available options for personalization will improve preference elicitation during the learning phase of the service personalization process by increasing understanding and certainty of preference selection by customers (Burton-Jones and Grange 2013). The degree of faithfulness of the representation is correlated with the achievement of the firm goals to: a) enable guests to identify all the preferences they desire, thus providing the firm with the information needed to offer an optimal service experience and b) maximize the number of customers that can communicate their preferences to the firm. Formally, we propose:

Hypothesis 1a. An IT-enabled CSS that produces more faithful representations during the learning phase of the service personalization process leads to increased users' preference elicitation.

Hypothesis 1b. An IT-enabled CSS that produces more faithful representations during the learning phase of the service personalization process leads to more users expressing preferences.

Outcome of IT-enabled service personalization

During the learning phase of the service personalization process, IT-enabled CSS helps individuals in more precisely specifying their requests, given the set of possible customizations made available by the firm. For service personalization to enhance the customer experience, the elicited preferences must inform the customization of the product or service during the matching phase. Thus, the task to be performed during the matching phase is the delivery, or fulfillment, of the preferences expressed by the customers during the learning phase. The performance of this "personalization fulfillment task" depends on whether the organization's employees can utilize IT-enabled CSS effectively to execute personalized service delivery (Goodhue and Thompson 1995). In an effective usage situation, system users should perform the tasks in the matching phase in a way that helps attain the organizational goals for using the system (Burton-Jones and Grange 2013;

Burton-Jones and Straub Jr 2006). While performance in the learning phase is defined by the comprehensiveness and precision of preference elicitation, the goal for using the IT-enabled CSS in the matching phase is improved service quality. That is, the firm engages in service personalization to improve customer value – defined as an "overall assessment of the utility of a product based on perceptions of what is received and what is given" by the recipient of the service (Zeithaml 1988, p. 14). In other words, those users who invest time and effort in specifying their preferences during the learning subprocess expect to experience a narrowing of the expectation-delivery gap when receiving and experiencing services customized for them (Parasuraman et al. 1985). As documented in the literature, the closer the gap, the higher the perception of service quality with a subsequent improvement in perceived satisfaction and value (Ho and Zheng 2004; Piccoli et al. 2017).

Following effective use theory, we posit that the above performance goal, as measured by increased customer value perceptions, depends on the service provider employees' effective utilization of the IT-enabled CSS (Burton-Jones and Grange 2013). Specifically, it is not enough for the system to capture and store faithful representations of customer preferences (learning phase), employees must customize the product or service accordingly (matching phase). However, the extent to which users act upon the faithful representations they obtain from the system (i.e., informed action) may vary by individual and over time. It is "how well the user is leveraging faithful representations obtained from the system in a task" (Burton-Jones and Grange 2013, p. 643) that determines performance outcomes. Informed action enhances task performance by enabling actions to "improve one's state in the domain" (Burton-Jones and Grange 2013, p. 644). In the context of service personalization, the informed action refers to employees' personalization fulfillment activities based on customers' requests (i.e., the task of matching). The greater the number of personalization requests from customers that are fulfilled by the employees, the smaller the expectation-delivery gap, and, in turn, the higher the users' perception of customer value received. Therefore, we hypothesize:

Hypothesis 2: The higher the level of employee's informed action during the matching phase of the service personalization process, the higher customers' perception of value.

4. Methodology

One of the contributions of our work is to use a field study, rather than a laboratory experiment, to investigate effective system use. We rely on archival data in the context of the lodging segment of the hospitality industry. This research setting is particularly well suited to the study of effective use in service personalization because hotels represent prototypical service businesses. Specifically, we gather data from a network of independently run three- and four-star hotels in Switzerland: Swiss Quality Hotels International (SQHI). In partnership with Innotour, a Swiss organization responsible for the promotion and development of the tourism sector in Switzerland, SQHI sponsored a project aimed at improving the personalization of guest experience in the participating hotels (Applegate et al. 2016). Participating hotels installed Hoxell, an IT-enabled CSS that includes a module for service personalization called MyPage. Innotour provided a grant subsidizing the set-up and implementation fees, for the applicants for two years. CLHS, developer of Hoxell, contributed to the financing of the endeavor by hiring two dedicated support staff who oversaw installations, training and support for the participating hotels (Applegate et al. 2016). Eight hotels were selected for the initiative, but only seven committed to the service personalization project. The hotels represent a range of sizes (from 45 to 106 rooms), segment focus (leisure and business) and locations (city and resort). The installation of the personalization module began on April 2015 for the first hotel and concluded on October 2015 for the last one. For each hotel, we gathered time series data spanning from six months prior to the introduction of the IT-enabled CSS (Hoxell) to twenty months after. This approach ensures sample comparability despite the different implementation dates.

Learning Phase

The project has several advantages for our research on effective system use in the context of service personalization. First, it standardizes the IT-enabled CSS used by all the participating organizations. Second, all SQHI hotels allow for special requests for personalization through a manual process, thus enabling a comparative test of preference elicitation during the learning phase of the service personalization process. During reservation, check-in, or at any time when a customer interacts with employees, the SQHI staff make guests aware of the possibility to express preferences (e.g., "if you have any other questions or requests, please do not hesitate to contact us," or "should you have any questions or requests, please dial 0 from your room"). The hotel employees annotate these special requests in a specific field of the Property Management System (PMS), called traces. Traces are then communicated to the appropriate department for fulfillment of the request during the matching phase of the service personalization process.

Upon installation of the personalization module of the IT-enabled CSS, each hotel added a new preference elicitation process. When guests receive a reservation confirmation, they are directed to a unique web page – MyPage – where they can select different options for personalizing their hotel stays. The SQHI hotels in the study provided a range of personalization items (from 52 to 133) – from preferred room temperature to pillow and bedding types, to drink, touristic amenities and so on. The preferences are laid out by categories with images and restrictions, thus serving as signifiers (Norman 2013; Piccoli et al. 2017) and making guests aware of the specific possibilities to customize their service experience (Figure 1). The two systems enabling preference elicitation during the learning phase, the traditional manual system and the IT-enabled CSS, differ on the three dimensions identified by representation theory (Table 1).

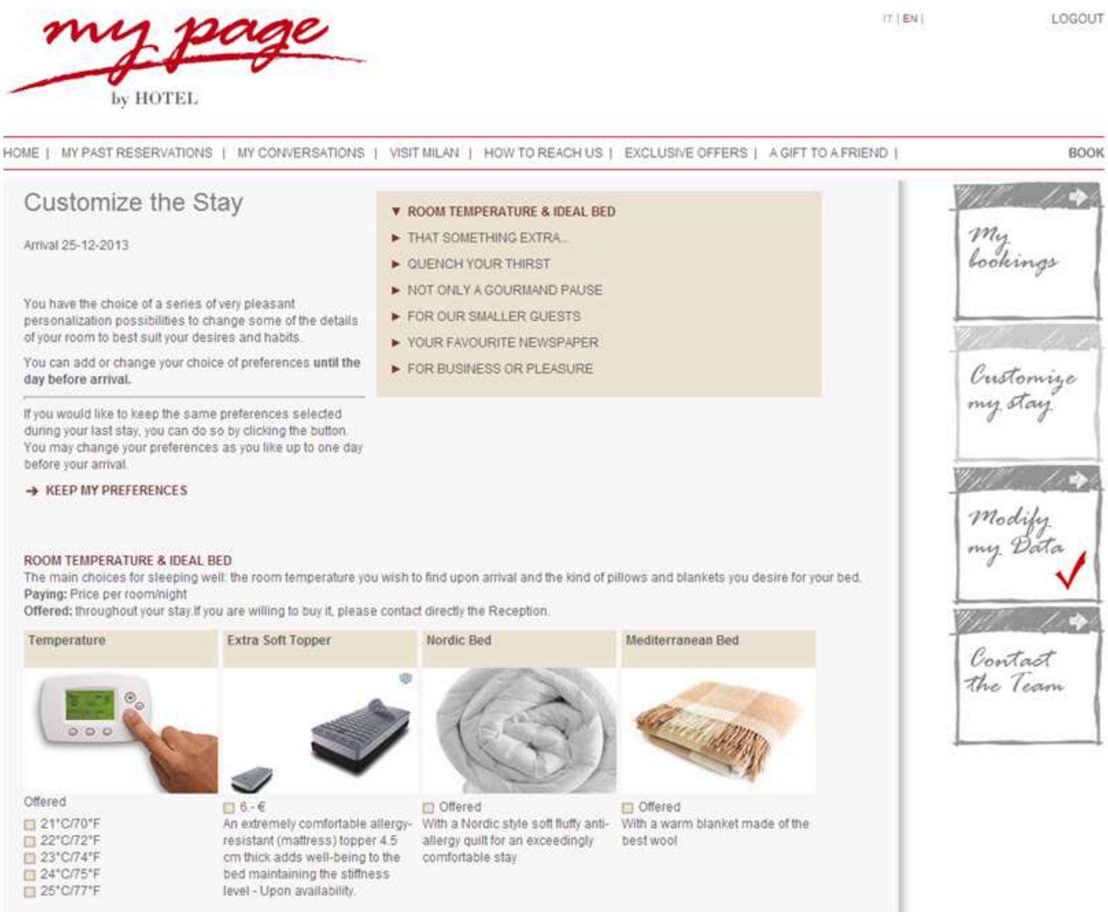

Figure 1: Personalization Functionality on MyPage

Table 1: Comparison of Traditional and IT-enabled CSS

Elements	Traditional Manual System	IT-enabled CSS (MyPage)
Physical structure	Telephone, fax, personal computers.	Personal computing devices (e.g., PC, tablet).
Surface structure	Open ended conversation with hotel staff, blank fax paper, blank email.	Web- or tablet-based browsing interface of the MyPage system.
Deep structure	Unstructured text or voice information. Individual	Structured information on MyPage website with signifiers

	representations of options emerge in each customer's mind.	and descriptions of available options (i.e., categories, images).

We argue that the IT-enabled CSS provides substantially higher degrees of faithful representation of personalization options than the traditional manual systems. Thus, we expect the number of items chosen by individuals using it to be significantly higher than those selected by customers using the traditional system (H1a). We also expect the IT-enabled CSS to stimulate an incremental number of users to personalize their experience – customers who would not otherwise do so (H1b).

Matching Phase

The process of delivering personalization requests during the matching phase of service personalization does not differ depending on how the preferences were elicited during the learning phase. On the day of guest arrival, rooms are assigned to each reservation by management. Using an iPad, the housekeepers responsible for preparing the rooms access the list of preferences associated with the reservation and deliver them to their respective rooms. Upon delivery of each personalized item the housekeeper marks the record as completed. Requested items that are not delivered remain unchecked (Figure 2, Figure 3).

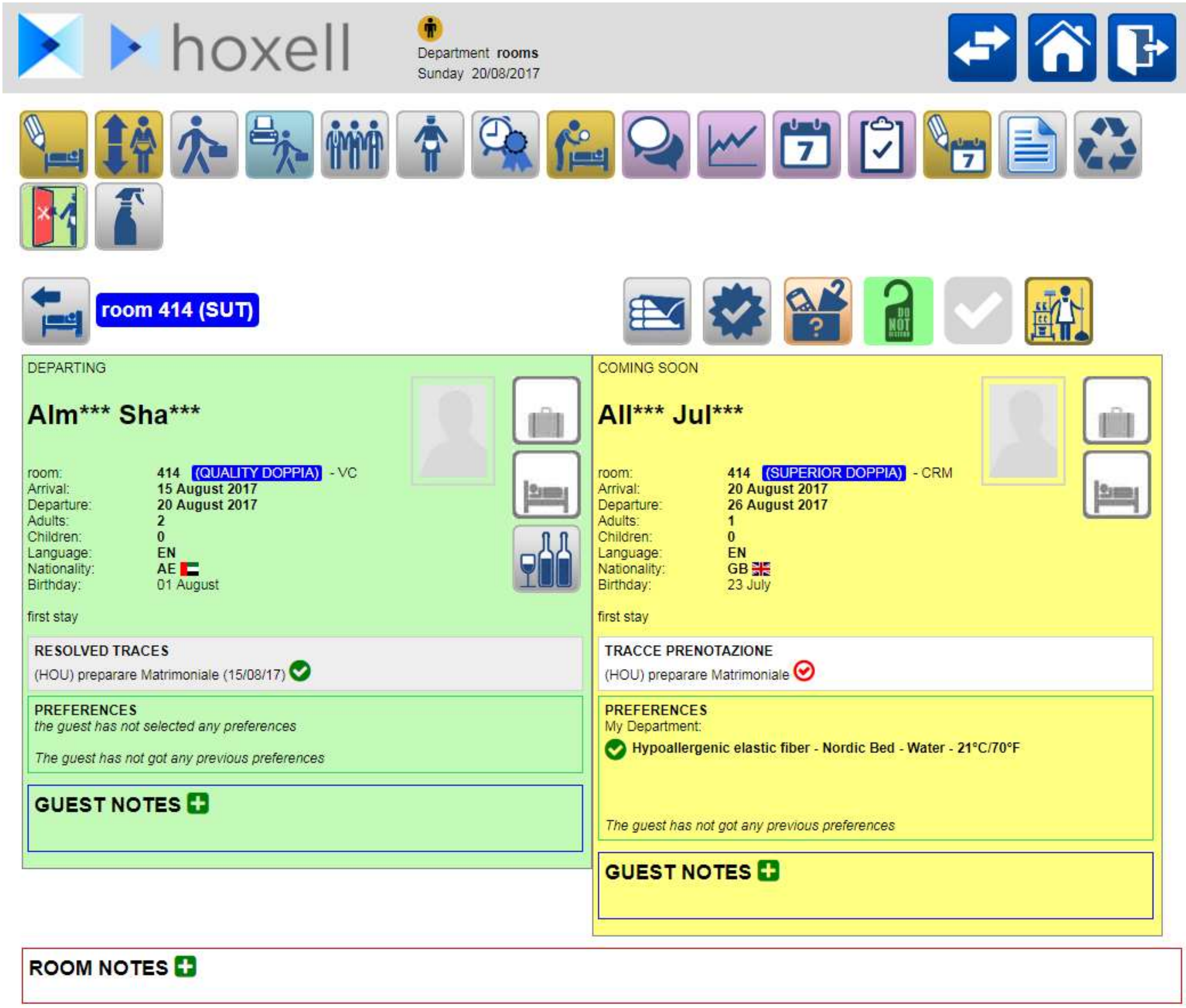

Figure 2: Preference fulfillment

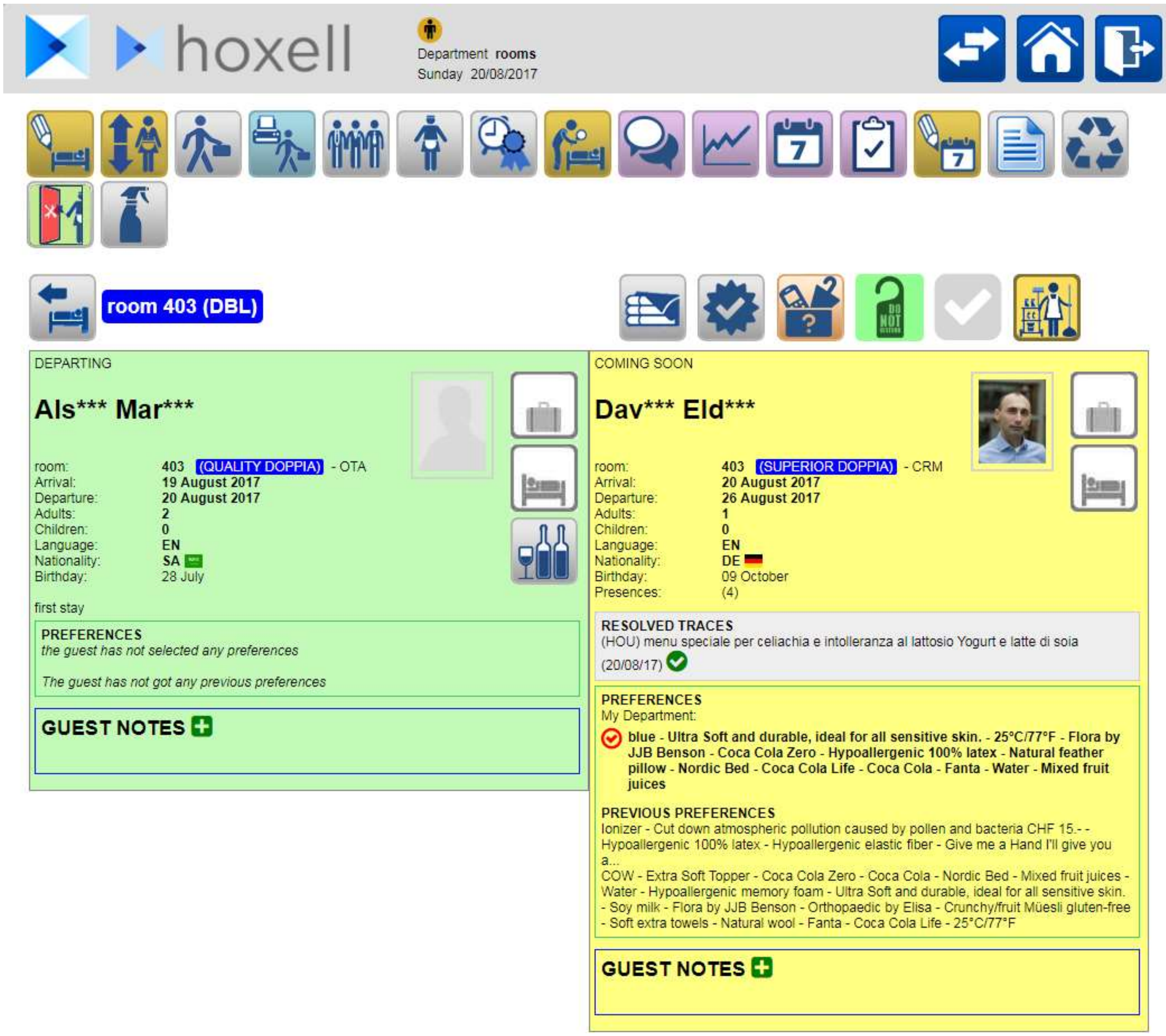

Figure 3: Preference fulfillment

We operationalize performance of the service personalization process (H2) as customer value. As service quality is subjective, rather than objective (Oh 1999), customer value is a perceptual measure. We extract customer value ratings from Booking.com because the website enables only verified guests who completed a stay at the hotel to rate their experience, unlike other major review sites (e.g., TripAdvisor). The review scores are assessed on a four-point ordinal scale with anchors: poor, fair, good, and excellent. An internal reservation number allows the matching of

Booking.com review data with reservation and personalization data from each participating hotel. The resulting complete records links customer value perceptions to their specific service experience, including whether they personalized their stays and how many items were in fact delivered to their rooms. The dataset is therefore uniquely suited to evaluate the performance of the service personalization process.

We operationalize informed action as the degree to which an employee leverages faithful representation of customers' preferences, as stored in the MyPage database, to provide customer value. The IT-enabled CSS we study requires that employees check-out specific personalized item requested (e.g., diet coke for the minibar, extra pillows) by a guest prior to placing them in the room. These data enable us to compute personalization delivery percentage (PDC): the ratio between the number of personalization items delivered and the number of personalization items requested by individual guests. Based on a strict definition of informed action we interpret PDC as a measure of "the extent to which a user acts upon the faithful representation he or she obtains from the system" (Burton-Jones and Grange 2013, p. 642). Housekeeping staff using the iPad to customize the room to the guest preferences use the system to identify what the customer requested (faithful representation), and deliver the items. Because all staff have access to the same application and there was no indication of any difficulties in accessing and understanding the personalization preferences, we ascribe variations in PDC to different degrees of informed action for each instance of personalization (i.e., each reservation). PDC is a measure of "how well the user is leveraging faithful representations obtained from the system in a task" (Burton-Jones and Grange 2013, p. 643) – that is, how accurately they perform the personalization fulfillment task during the matching phase. Note that it is beyond the scope of our work to investigate the *determinants* of informed action. Rather we seek to establish the relationship between effect and performance – link 1b in Burton-Jones and Grange (2013) general framework on effective use. Thus, we do not investigate why staff may engage in different degrees of informed action.

Consistent with recent work in the service personalization literature we control for the following potential confounding factors: average daily room rate (ADR), length of stay in days (LOS), price paid for personalized items (PPrice), number of adults and children for each reservation (Piccoli et al. 2017) (Piccoli et al. 2017).

5. Data Analysis and Results

The dataset contains 118,647 reservations spanning a period of 26 months from the seven SQHI hotels participating in the service personalization project (Table 2).

Table 2 SQHI hotels summary

Hotel	Hotel type	Booking.com score	N. of stays	N. of personalized stays	IT-enabled personalization (% of all personalized stays)	Time frame
ABC	4 stars	9.0 / 10	17,121	1,000	75.90	10.14 – 12.16
Belvedere	4 stars	8.8 / 10	15,165	1,511	58.97	01.15 – 03.17
Belvoir	4 stars	8.9 / 10	17,584	1,187	35.97	03.15 – 05.17
Cascada	4 stars	8.6 / 10	20,526	2,216	74.10	12.14– 03.17
Derby	3 stars	8.7 / 10	15,289	580	21.21	12.14 – 03.17
Sedartis	4 stars	8.5 / 10	12,461	715	40.98	02.15 – 04.17
Seehotel	4 stars	9.0/10	20,501	549	11.29	05.15 – 05.17

From the total sample, 7,756 reservations contain at least one service personalization request, with 54.11% (4,197 reservations) elicited through the IT-enabled CSS and the remainder through the traditional manual process (Table 3).

Table 3 Summary statistics

	Mean	S.D.	Min.	Max.
Total stays[a]	631.1	214.29	47	1517
Personalized stays (traditional)[a]	18.8	14.08	0	94
Personalized stays (virtual)[a]	28.75	27.26	0	107
Items requested per stay (physical)	1.05	0.23	1	3
Items requested per stay (virtual)	3.77	3.26	1	29

[a] – Monthly data

Prior to testing for Hypotheses 1a and 1b, we test for differences between hotels. We detect no significant difference in the number of personalized items requested per stay between the hotels ($\chi^2 = 0.68$ with 6 degrees of freedom). Thus, we test H1a with a fixed effect model without any random component. We used a Poisson regression with log link:

$$\ln(\mu_i) = \beta_1 + \beta_2(MyPage_i)$$

We model the expected number of personalized items requested by a guest (μ_i), with $i = 1, \ldots, 7756$. *MyPage* is a dummy variable representing the method of service personalization with 1 denoting IT-enabled personalization and 0 denoting traditional methods. Our results support the hypothesis that preference elicitation by customers increases in the IT-enabled service personalization system (p-value < 0.01).

Table 4 Poisson regression results

	Coefficient	S.D.	z-value	p-value
Intercept	0.05308	0.01632	3.252	0.00115
MyPage	1.27339	0.01816	70.130	< 0.001

On average, the guests requested 1.05 personalized item with traditional methods and 3.77 personalized items using MyPage (Figure 4). Thus, the IT-enabled CSS elicits, on average, 3.56 times more preferences than the traditional manual system (Table 4).

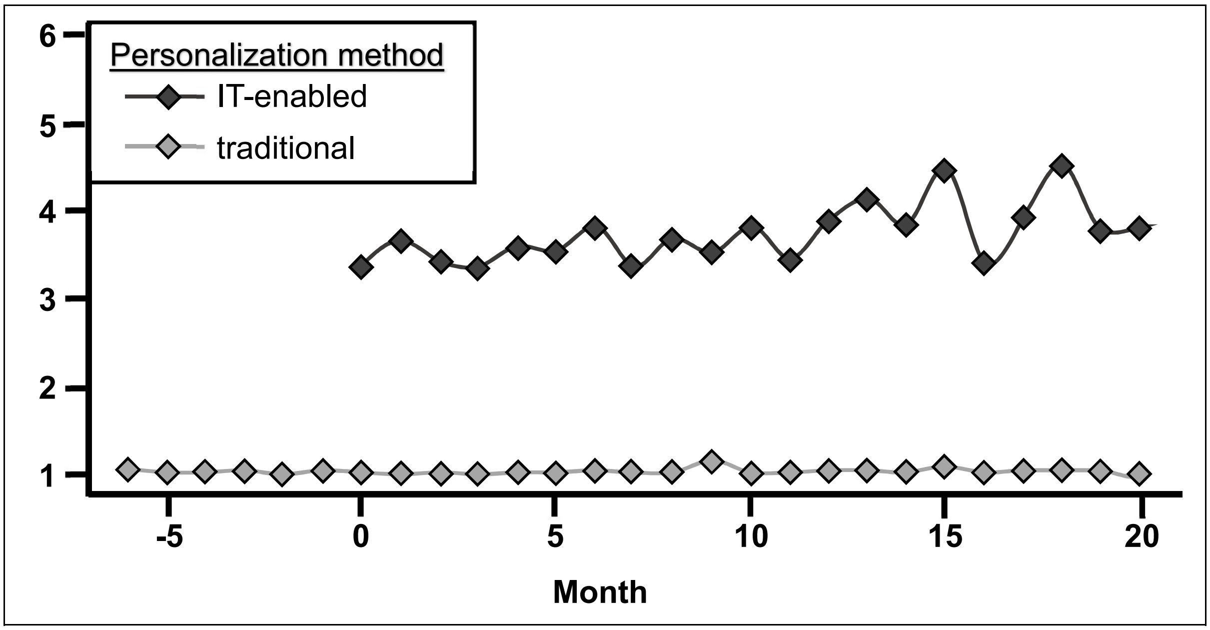

Figure 4 Average number of personalized items requested per stay for SHCI hotels

To measure the effect of the IT-enabled service personalization on the number of customers expressing personalization preferences (H1b), we estimate the proportion of guests engaging in service personalization – via the traditional manual system and the IT-enabled CSS (Figure 5).

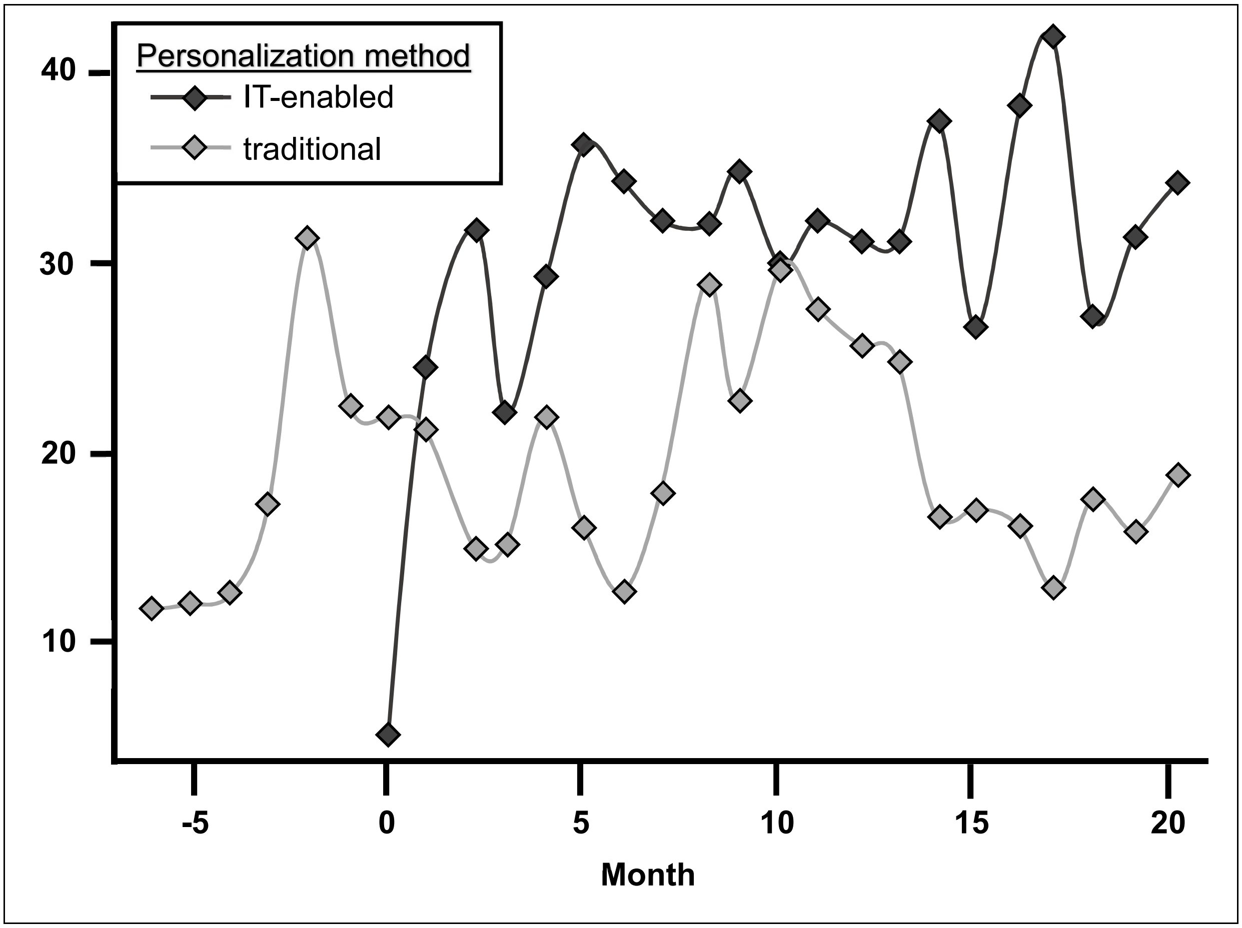

Figure 5 Average number of personalized items requested per stay for SHCI hotels

We detect a significant difference among the hotels in the number of customers who personalize their stay ($\chi^2 = 65.95$ with 6 degrees of freedom, p-value < 0.001). We therefore control for the random effect attributable to the hotels by using a mixed-effect binomial regression with logit link:

$$logit\left(P\left(Personalization_{ij} = 1\right)\right) = \ln\left[\frac{P\left(Personalization_{ij} = 1\right)}{1 - P\left(Personalization_{ij} = 1\right)}\right]$$

$$= \beta_1 + \beta_2\left(MyPage_j\right) + \beta_3\left(Implementation_i\right) + U_{0j}$$

We model the proportion of personalized stays, $Personalization_{ij}$, with $i = 1, \ldots, 118{,}647$. Subindex j = 1 indicates personalization via the IT-enabled process, while subindex j = 0 indicates personalization via the traditional process. Consequently, the dummy variable $MyPage_j$ assumes a value of 1 for subindex j = 1 and 0 for subindex j = 0. $Implementation_i$ is a dummy variable with value of 0 for the months before the introduction of the IT-enabled CSS and 1 for the months after implementation. $Implementation_i$ serve to measure any cannibalization effect following the introduction of IT-enabled personalization. A significant negative coefficient for $Implementation_i$ would suggest that users are switching from the traditional manual process to IT-enabled service personalization.

Table 5 Mixed-effect binomial regression

Predictor	Coefficient	Std. deviation	z-value	p-value
Intercept	-3.57903	0.14586	-24.537	<0.001
MyPage	0.01738	0.41400	0.042	0.9665
Implementation	0.10922	0.04459	2.450	0.0143
Random effect of hotel on the fixed effect of MyPage				
	Variance		S.D.	
Intercept	0.1374		0.3707	
MyPage	1.1923		1.0919	

Our results provide support for the H1b (Table 5). After controlling for the idiosyncratic effects ascribable to each hotel, we detect no significant effect of *MyPage*. This result indicates that there is no difference in the proportion of customers who personalize using the traditional process and the IT-enabled CSS. There is a significant positive effect of *Implementation* ($p\text{-value} < 0.05$). These results show that there is no cannibalization of the IT-enabled personalization process over the manual one. Rather the two are synergistic. In other words, users who personalize their experience via the IT-enabled CSS are incremental and, after the implementation of the IT-enabled personalization process, the number of customers using the traditional personalization method increases by a factor of 1.12.

To test Hypothesis 2, we first establish the main effect of personalization on customer value. We do so with a set of 2,497 reservations that could be linked to reviews posted on Booking.com (Table 6). This dataset enables us to test differences in customer value, as reported on Booking.com, by whether the guest had personalized the experience.

Table 6 Distribution of value rating on Booking.com

	No response	Poor	Fair	Good	Excellent
Number	19	110	351	1230	787
Percent	0.76%	4.41%	14.07%	49.26%	31.52%

We detect a significant difference between the hotels in customer value ($\chi^2 = 51.39$ with 18 degrees of freedom, p-value < 0.001). We model the main effect of personalization using a multilevel logistic regression using typical control variables (Table 7).

Table 7 Summary statistics

	Mean	S.D.	Min.	Max.
ADR	276.28	122.67	8.5	1450
LOS	1.88	1.28	0	10
PPrice	22.6	14.93	0.5	120
Adults	1.94	0.54	0	5
Children	0.16	0.49	0	3

We model customer value rating (j index = 1, …, 3) for each reservation in the sample ($i = 1, \ldots, 2{,}497$).

$$P\left(Value_j\right) = \theta_j + \beta_1(MyPage_i) + \beta_2(ADR_i) + \beta_3(LOS_i) + \beta_4(Adults_i) + \beta_5(Children_i) + U_{0j}$$

Our results suggest that, after controlling for ADR, LOS, PPrice, number of adults and children for each reservation, there is no significant main effect of personalization usage on the perceived customer value rating for each service experience (Table 8). While this result is inconsistent with previous literature (Piccoli et al. 2017) a formal test of Hypothesis 2 explains the inconsistency.

Table 8 Effect of personalization on customer value

Predictor	Coefficient	Std. deviation	z-value	p-value
MyPage	-0.0616	0.1140	-0.5405	0.588850
ADR	-0.2567	0.0516	-4.9781	<0.001
PPrice	-0.0027	0.0072	-0.3778	0.705604
LOS	-0.0124	0.0322	-0.3863	0.699257
Adults	0.1677	0.0837	2.0034	0.045139
Children	0.1678	0.0871	1.9259	0.054111
Random effect of hotels				
Variance		Std deviation		
0.01770505		0.1330603		
Thresholds				
	Coefficient	Std. deviation	z-value	
2.5|5	-2.8030	0.2484	-11.2851	
5|7.5	-1.1826	0.2329	-5.0770	
7.5|10	1.0873	0.2331	4.6653	

We test Hypothesis 2 using the subset of reservations for which we have both customer value perceptions and personalization delivery percentage (PDC). We reduce the sample to the stays which had requested at least one personalized item. We identified 343 such reviews in six of the hotels (Table 9).

Table 9 Proportion of value rating by the percent of personalization delivery

Personalization	Number of Stays	Average customer Value	Average personalization delivery
None	2154	7.65	NA
MyPage (PDC < 0.4)	28	7.23	8%
MyPage (0.4 < PDC < 0.6)	12	7.29	48%
MyPage (PDC > 0.6)	303	7.75	99%

We model the effect of informed action on customer value using a multilevel logistic regression and control for reservation level confounds as well as systematic differences between the hotels

(*HotelPDC*). We model customer value rating (j index = 1, …, 3) for each reservation in the sample (i = 1, …, 343):

$$P(Value_j) = \theta_j + \beta_1(PDC_i) + \beta_2(ADR_i) + \beta_3(LOS_i) + \beta_4(Adults_i) + \beta_5(Children_i) + \beta_6(HotelPDC_i) + U_{0j}$$

Our results indicate that there is a significant positive effect of PDC (p-value < 0.05) on customer value. There is a marginal random effect of hotel with variance between the venues equal to 0.02. More importantly, the effect of PDC is significant only at the level of individual stays, with no systematic differences between the hotels. In other words, the main effect of PDC on perceived customer value is stable across hotels (Table 10). These findings lend support for H2. Specifically, a one-unit increase in PDC more than doubles (2.37) the likelihood that customers will rate the experience higher. In other words, a guest who receives 100% of the requested personalization is 2.37 times more likely to give a higher level of value rating (e.g., from fair to good or from good to excellent) on Booking.com to the hotel as compared by a customer who received 0% of her requests delivered.

Table 10 Effect of personalization delivery percentage on customer value

Predictor	Coefficient	Std. deviation	z-value	p-value
PDC	0.8659	0.4016	2.1560	0.03108
ADR	-0.4437	0.1435	-3.0929	0.00198
PPrice	-00.062	0.0177	-0.3496	0.72666
LOS	-0.0100	0.0819	-0.1223	0.90267
Adults	0.5108	0.2444	2.0894	0.03667
Children	0.0383	0.1884	0.2036	0.83869
HotelPDC	1.1452	2.4611	0.4653	0.64170
Random effect of hotels				
Variance		Std deviation		
0.01535012		0.1238956		
Thresholds				
	Coefficient	Std. deviation	z-value	
2.5|5	-0.8082	2.0436	-0.3955	
5|7.5	1.0891	2.0338	0.5355	
7.5|10	3.6280	2.0552	1.7653	

6. Discussion

Our work contributes to the development of representation theory and its application to understanding information systems effective use. We claim both theory extension and intension. First, we extend representation theory by providing its first application in the area of IT-enabled service personalization. The representation model posits that grammars used to generate clear, complete scripts are the focal point of a faithful representation of real-world phenomena (Wand and Weber 1993). We apply this notion to the generation of grammars for service personalization. Thus, the signifiers (Norman 2013) used in the myPage application served as the grammars for the creation of possible personalization options with pictures and descriptions (i.e., scripts) that structurally represented the choice for customers. These representations were superior to those available in the traditional manual system and were aimed at enhancing both customers' ability to express their needs and the firm's ability to learn the guest preferences. As a result, customers' preference elicitation measurably improved, leading to a significant increase in the number of preferences elicited from each customer (H1a) and the number of customers expressing preferences (H1b).

With respect to intention, our contribution consists in refining the concept of informed action (Burton-Jones and Grange 2013) in the context of IT-enabled customer service. We further empirically validate the role of informed action in achieving performance goals in terms of customer value. Our results lend support to the causal link between effective use and performance (Burton-Jones and Grange 2013). Specifically, we isolate informed action as the extent to which employees act upon the available representations in the system (i.e., customer preferences) when performing the personalization fulfillment task. Our findings support the hypothesized relationship between employees' effective use and the outcome that the IT-enabled CSS is designed for: improving perceived customer value (H2).

The focus of our paper is on representation theory and its application to understanding the direct link between effective system use in firm performance. Our findings indicate that informed action contributes to performance and should therefore be an important consideration during system design and implementation. However, we do not investigate the determinants of informed action. It is also important to note that while the focus of the study is on informed action, it is not possible to have informed action without transparent interaction and faithful representation (Burton-Jones and Grange 2013). Transparent interaction and faithful representation relate to the technology capability of representation and user capability of presentation (information giving) and elicitation (information seeking) (Serrano and Karahanna 2016). The users' competencies in information giving and seeking have a compensatory interaction effect with the system's representation capability and enhance task performance (Serrano and Karahanna 2016). Therefore, any users' lack of competencies will affect the task performance. This is consistent with Burton-Jones and

Grange (2013) proposed driver of informed action: learning to leverage representations. When the users learn how to leverage the information, the users are more likely to exhibit informed actions.

Future research should broaden the perspective we take in this work and investigate the other dimensions of effective use. Specifically, in our study there are no systematic differences in informed action at the hotel level. Moreover, all employees used the same system – Hoxell software on iPads – and there were no systematic differences in training or representational fidelity. However, we did observe difference in informed action. This observation begs empirical testing of the underlying drivers of informed action.

7. Conclusions

As with any archival study, there are a number of limitations that must be recognized during the interpretation of results. Given our inability to directly survey customers, we rely on the available single item measure of customer value exposed by Booking.com. While this is not optimal, what we use is the measure of customer value published by one of the dominant travel review website. Online review ratings have been shown to directly influence price premiums and firm market share (Anderson 2012). Thus, the measure we use is a critical one that influences performance outcome for hotels. Generalizability of our findings may be limited. We collect data on seven firms, and our work is narrowly focused on the lodging segment of the hospitality industry. The lodging sector is a prototypical service businesses and our findings may be generalizable to service processes in other industries. However, our work provides a narrow test of representation theory and effective use, and future replications in other contexts are warranted.

Previous empirical studies established the connection between quantity of system usage and firm performance (Devaraj and Kohli 2003; Paré et al. 2015). However, while theory has long recognized that information technology does not generate value by itself (Kohli and Grover 2008), we are not aware of any empirical work expressly modeling effective use in the context of IT-enabled CSS. Despite the inevitable limitations, to our knowledge, ours is the first empirical field study focused on the link between effective use and system performance.

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