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Switching intentions in the context of open-source software movement: The paradox of choice

David John Lemay[1] · **Ram B. Basnet**[2] · **Tenzin Doleck**[3]

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Abstract
Open-source software movement presents a viable alternative to commercial operating systems. Linux-based operating systems are freely available and a competitive option for computer users who want full control of their computer software. Thus, it is relevant to inquire on how the open-source movement might influence user technology switching intentions. The current study examines user intentions to switch to a Linux-based open-source operating system. Using partial least squares modeling, we examine the influence of inertia, (i.e., status quo bias), benefit loss costs, incumbent systems habit, procedural switching costs, sunk costs, social norms, and uncertainty costs, on perceived need and behavioral intention. We find that Perceived Need and Behavioral Intention ($\beta = 0.691$, $p < 0.001$) exhibited the strongest relationship followed by Social Norms on Perceived Need ($\beta = 0.508$, $p < 0.001$) and Uncertainty Costs on Inertia ($\beta = 0.451$, $p < 0.001$), with small effects from Incumbent System Habit and Perceived Switching Cost on Inertia as well. As cross-sectional research, no causal interpretations are permitted. Modelling user switching intentions can help facilitate user service design and software documentation efforts by concentrating on user needs. Overall, we find that the results support inertial effects and the influence of social norms on perceived need and users' switching intentions. Implications of these findings are also discussed.

Keywords Technology acceptance · Switching intentions · Open source software · Linux operating system

✉ Tenzin Doleck
tdoleck@sfu.ca

Extended author information available on the last page of the article

1 Introduction

The open-source ethos of computers has arguably been around since humanity's earliest conception of computing machines. Indeed, the commonly noted earliest software source was published openly as an addendum (Menabrea et al., 1843). However, its contemporary incarnation was spurred by the conception of GNU General Public License (GNU GPL) software movement in the 70s and 80s (Jensen, 2019) and popularized by the hacker libertarian ethos that developed among computer engineers and users toward full control of their machines (Margan & Candrlic, 2015). Open-source remained a fringe phenomenon as the primary user base remained producers of computer technology whereas the majority of personal computer users have always been consumers only; or active versus passive users in Van Vliet's (2008) model of open-source software development. Perhaps spurred by the democratizing effects of the internet, full-featured open-source alternatives (Silic & Back, 2017) have become available over the last twenty years. As a testament to the growing saliency of open-source software, Daniel et al. (2018) highlight that "the success of open source software (OSS) development has led a growing number of companies to seek to leverage this model of development" (p. 1070). In fact, von Krogh and Spaeth (2007) note that "the open source software phenomenon has had a ubiquitous impact on society and the economy" (p. 242). Developed with the consumer in mind, they come with modern GUIs and are designed for easy use. Today many open-source alternatives rival commercial products and in some cases the open-source tool has become the standard. This is especially true of the internet where a majority of web servers now run Linux instances (Finley, 2016).

Linux is considered a milestone in the open-source software development movement (Kuwabara, 2000). Linux distributions are now fully supported in various hardware platforms and are in use in various industries and contexts (Xiao et al., 2019). In fact, the Linux kernel today is integrated in numerous consumer operating systems (OSes) such as Ubuntu, RedHat, and Fedora, with various desktop packages like KDM, Mint, offering similar user experiences as found in Windows and Mac commercial software products. These open-source alternatives offer advantages over commercial operating systems for the adventurous. Linux-based distributions are fully customizable to the point that some users even build fully customized operating systems. Using an architecture like Arch, a user can build OSes completely to specification, say, optimizing for speed, size, or using Kali for information security—allowing for full control of the software running on your system. In fact, in recent years, organizations and individuals have been transitioning from proprietary solutions (e.g., Microsoft OS) to open-source solutions (Linux OS) (Silic & Back, 2017).

Whereas open-source was fringe in previous decades, today it is increasingly mainstream and not just the preserve of the geek. Open-source software, available in one-click installs, is now accessible to a wide swath of non-specialist users. However, it remains infused with a political movement; open-source remains a choice and also a political statement. In the battle to maintain a free internet (World Wide Web Foundation, 2018), supporting open-source software movement is a vote for the freedom and access to information for all. Despite the popular emergence of open-source software such as Linux, relevant research examining users' motivations for adopting this software still lags. The literature is rife with studies on technology acceptance (Tao et al., 2020). Indeed much of the literature has been focused on technology adoption and diffusion (Gong et al., 2020). In contrast, however, "few studies have investigated the determinants of the behavioral intention to upgrade" (Wang et al., 2018, p. 7). Others have also noted this gap in the literature; for example, Kuo (2020) note that "user switching behaviour has been paid limited attention as yet" (p. 1). In fact, there is scarce research on providing a structural model of students' intentions to switch to a Linux-based operating system. Given the preceding, what is unknown is how such political discourse might influence individuals' switching intentions from commercial OSes toward open-source Linux-based OSes. Prior work has been silent on the factors that motivate users to switch to open-source OS. Accordingly, the research objective of the present study is to uncover the antecedents to switching intentions to Linux-based OS. We adopt the technology upgrade model to guide the research model and investigation.

The remainder of the paper is organized as follows. In Section 2, we review the literature related to our study. We then provide the research objectives and questions in Section 3. Afterward, in Section 4 we provide the method. In Section 5, we present the study's analytical procedure and findings, and interpret the results. Finally, we conclude with a discussion of the present study's findings, implications, limitations, and future research directions in Section 6.

2 Literature review

2.1 Technology acceptance and switching intentions

The psychological literature around technology acceptance and switching intentions has been examined in the light of theories of innovation diffusion, process theories of decision making such as rational choice, reasoned action, and planned behavior (Ajzen, 1991; Fishbein & Ajzen, 2011); intentional-motivational theories including dual process drive theories (Bargh & Ferguson, 2000; Leventhal, 1970); and self-concept theories such as self-determination (Ryan & Deci, 2000), social cognitive (Bandura, 1986) and other theories of personality and individual differences. These theories assume by and large a rationally acting individual and deliberative, conscious behavior and action (Ajzen & Fishbein, 2005) and place less focus on social influences of cognition and behavior, save to the extent that it informs rational processes (Bargh & Ferguson, 2000). In psychological research conducted in the attitude-intention-behavior axis, the role of cognitive appraisals (i.e., conscious, rational) predominate as decisions and behaviors related to technological adoption and switching intentions are held to result from conscious, effortful thought and directed at optimizing specific value functions such as usability, usefulness, or as satisfying specific needs and drives (Bhattacherjee & Premkumar, 2004).

Whereas rational decision theories like reasoned action, planned behavior, and innovation diffusion recognize the influence of various background factors, like subjective norm (Venkatesh et al., 2003) or perceived behavioral control, the core models remain relatively parsimonious but are readily augmented with factors salient to the specific context. As has been argued in specifically in the case of technology acceptance model (Doleck et al., 2016; Lemay et al., 2017, 2019), a situated perspective (Greeno, 1998) recognizes that situational factors are varied and can moderate core relationships. This is explained as resulting from the reflexive relationship that can arise between technology and activity, as technology is not only the tool for the accomplishment of an activity but often determines the nature and contours of the activity itself; as with the emergence of online political engagement and the legitimization of public discourse on mobile messaging platforms (Lemay et al., 2019).

Indeed, participation in certain social activities may be dictated by access and engagement with such online social media platforms. Such social considerations exert influence above considerations of control, goal orientation, or normative beliefs, and suggest a more complicated picture where situational factors interact with individual cognitions to inform technology acceptance beliefs. A situated perspective recognizes the contextual nature of technology acceptance and use; antecedent beliefs influence technology acceptance through other dimensions than cognitive appraisals including social and affective dimensions. A situated perspective recognizes that social and affective factors must also be considered for a fuller account of technology acceptance decisions. It is a strength of TAM and other reasoned actions theories that their general parsimonious structure can be augmented with local, contextually-specific factors for specific situations (Lemay et al., 2018). Further, the theory of reasoned action recognizes that both explicit and implicit beliefs, biases, and prejudices can influence attitudes and beliefs (Ajzen & Fishbein, 2005). Consideration of social and affective dimensions can be accommodated regardless of whether they result from explicitly deliberative reasoning or more implicit processes.

In similar fashion, studies of switching intentions can be extended by invoking a situated understanding wherein switching intentions may also be influenced by non-deliberative appraisals resulting from affective or social factors other than subjective control or normative beliefs elicited by situations and contexts of use. In the context of user switching intentions for Linux OSes, studies might also consider the specific socio-political context informing the open-source movement to account for the influence of situation on technology acceptance and use. Systematic situational research can help elucidate the structural effects influencing technology switching intentions beyond strict rational appraisals of technology in terms of expectancies and disconfirmations influencing satisfaction (Bhattacherjee et al., 2012; Bhattacherjee & Premkumar, 2004).

Switching intentions investigations should begin by recognizing the often symbiotic relationship existing between social activity and the conditions of technology use and the social and affective dimensions of individual technology switching intentions. Few studies of user switching intentions have been conducted in the social influence processes perspective over the last thirty years. Although Fan and

Suh (2014) reviewed the research on disruptive technologies and their capacity to refashion activities and relationships, their study was limited to cognitive determinants of expectation and disconfirmation, finding that switching intentions were positively influenced by expectations for disruptive technology and by disconfirmation of incumbent technology. However, other studies have highlighted the influence of subjective norm on technology switching intentions (Bhattacherjee & Premkumar, 2004; Liu et al., 2016) highlighting the importance of social influence processes in technology switching intentions.

2.2 Social influence processes and technology switching intentions

Studies of social processes involved in influence and social movements have documented vectors of social change and these help to understand how social norms evolve by modelling the dynamics of in-group and out-group, from the fringe to the center, and how ideas spread (Martin & Hewstone, 2007). What is clear is that social change processes can occur quite suddenly, as documented in consumers' changing perceptions of mobile phone technology. Following the introduction of smartphones, users were initially drawn to specific features, and Nokia maintained a robust consumer base; however, in a short period, Nokia's feature phones were eclipsed by the feature-rich application ecosystems of the Apple OS and Google Android mobile platforms (Nykänen et al., 2015).

Most studies of technology switching intentions have relied on a cost-benefit rational choice cognitive models focusing on factors like habit, inertia and resistance to change or they considered the influence of social factors such as subjective norms on expectations and disconfirmation (Bhattacherjee & Premkumar, 2004; Gerlach et al., 2014; Liu et al., 2016). Others considered a push-pull-mooring 'migration' model (Bansal et al., 2005; Nykänen et al., 2015). The migration approaches proposed accounts of the way beliefs and perceptions support status quo, favoring the incumbent over the challenger, through the concept of e-loyalty. However, costs have been weighed in relation to the technology use in the organization and not other social considerations such as group membership, identification, and participation. While it appears switching intention studies have not examined the social dimension beyond normative beliefs, this ignores the very real political dimension of majority and minority influence and social competition. However, we recognized today that technology use is not simply a function of usability or usefulness but of powerful social determinants as demonstrated by the influence of technology platforms on social and political institutions such as fake news, cyber and information warfare. Though proponents of technology have long argued that technology is neither good nor bad but only a tool. Few would dispute today that technology use is undeniably moral and increasingly has the power to shape society. In this contested grounds, the choice of open-source technology is often characterized as a vote for a democratic future. Freedom of information and access to technology are defended on the values of democracy, liberty and equality of opportunity. Closed commercial platforms are associated with exploitation and control and increasingly economic gains are hoarded by a select few. Thus it appears important to consider the multidimensionality of user switching intentions as attitudes and behaviors are influenced by cognitive and affective dimensions but also by social, cultural, historical, and political dimensions (Lemay et al., 2019).

In the context of technology switching intentions, other factors outside the technology must be sought from the above dimensions, as technology switching is likely influenced by social, affective, and economic (see political) considerations. Recently, Wang et al. (2018) argued that such factors which tend toward supporting the status quo can be conceived as enforcing an inertia on user intentions. Inertia is similar to the notion of habit which influences user perceptions and behaviors (Limayem et al., 2007) and influences the status quo (Kim & Kankanhalli, 2009). Inertia is likely to be subject to a kind of phase transition, meaning that behaviors that are consistently normative and value-maximizing can change all at once from the introduction or diffusion of innovation or social influence. The examples of such "disruptions" are rife in today's world, from social unrest and mass political movements, to new forms of violence aimed at disseminating terror and dominating media feeds to the changing media landscape and public discourse around social justice and minority rights and representation. Changing social norms and behaviors become powerful motivators for reassessment and change in individual behaviors and beliefs too (Bansal et al., 2005; Nykänen et al., 2015). As with its physical analogue, inertia is an acting force and ought to be conceptualized not simply as a drag but as the momentum of social groups which change through feedback processes and collective activity and can be markedly non-linear. Thus, social influence processes are powerful determinants of individual attitudes and behaviors.

3 Research objectives

In the present study, we sought to assess the differential relationship of inertia and social norm on perceived need and behavioral intention to switch to a Linux-based open-source operating system. In the present study, we elected to study Linux as an open-source operating system because it is the most popular open-source operating system (Vaughan-Nichols, 2020) and because it is has been shown to be on par or even better than propriety offerings in many aspects of performance (Kuwabara, 2000).

Social norms and inertia result from social influence processes. As Martin and Hewstone (2007) wrote in their chapter for the *Sage Handbook of Social Psychology*, "Social influence refers to the ways in which the opinions and attitudes of one person affect the opinions and attitudes of another person. Although influence can occur between individuals, it is widely seen to operate in the context of social groups, where group members are continually influencing each other through the dynamic formation and change of group norms. Two forms of social influence can be identified within groups, which serve the function of either maintaining group norms (social control) or changing group norms (social change). (p.312)" Social norms are influenced by dynamic group processes and can either exert a force towards conformity and status quo, or towards change. Conceived hence social norms are not monolithic or static; social norms change from group to group and over time. Further, Martin and Hewstone (2007) write: "processes of social change typically originate from a small subsection of members of the group, and, therefore, the process is often referred to as minority influence. Without active minorities, group opinions would never be challenged, fashions would not change, political campaigns would never succeed, and innovations would be thwarted" (p. 312). Thus, social norms and inertia can be conceived as social influence forces toward conformity but also toward change.

Our model is elaborated in the dual process perspective as we see behavioral intention affected by perceived need, on the one hand, and inertia, on the other. We extend this perspective by considering social and affective factors that view user behavior as being influenced not only by rational appraisals but also fallacies like sunk costs, uncertainty, habit, and also social determinants of normative behavior.

3.1 Research question and hypotheses

Previous work has primarily focused on technology adoption and diffusion (Gong et al., 2020). The present study addresses the gap in the literature by shifting the focus on switching intentions. Our overarching research question was formulated as follows:

"How are user perceptions of inertia, incumbent system habit, and inherent costs related to perceived need and behavioral intention to switch to a Linux-based operating system?"

In order to address the research question, we examine twelve hypotheses that help provide a picture of the antecedents to switching intentions to Linux. The hypotheses we study in this paper are undergirded by the theoretical framework of the technology upgrade model (Wang et al., 2018). Following Wang et al. (2018), the hypotheses are enumerated as follows:

H1: Inertia has a negative relationship with behavioral intention
H2: Perceived need has a positive relationship with behavioral intention
H3: Benefit loss costs have a positive relationship with inertia
H4: Incumbent system habit has a positive relationship with inertia
H5: Procedural switching costs have a positive relationship with inertia
H6: Sunk costs have a positive relationship with inertia
H7: Social norms have a negative relationship with inertia
H8: Uncertainty costs have a positive relationship with inertia
H9: Benefit loss costs have a negative relationship with perceived need
H10: Procedural switching costs have a negative relationship with perceived need
H11: Social norms have a positive relationship with perceived need

3.2 Research model

Rational choice theory for the most part assumes complete information, however, individuals often act with incomplete information and insufficient means. In these situations, heuristics are prone to break down and we are more susceptible to an increased range of biases (Tversky & Kahneman, 1974). Hence, our model considers a range of behavioral influences from social determinants to fallacies and errors in judgements. Individuals are prone to bias in judgement as with the sunk cost fallacy, that is, individuals' aversion to cutting loses. Inertia is defined as a forceful preference for the status quo. Thus, inertia is influenced by uncertainty, procedural switching costs, (e.g., the cost of learning a new operating system), sunk costs, incumbent system habit (i.e., preference for current system); all which favor present circumstance over a change of circumstance. Social norm is defined as a preference for alignment or conformity with the social group. Social groups and processes are especially prone to influence (Martin & Hewstone, 2001). Thus, social norms are theorized to have a positive relationship with perceived need and inertia a negative relationship with behavior intention. In Fig. 1 below, we present our research model with hypothesized path relationships. The constructs in the research model include: behavioral intention (BIU); Inertia (INT); Perceived need (PND); Benefit loss costs (BLC); Incumbent system habit (ISH); Procedural switching costs (PSC); Sunk costs (SCT); Social norms (SNM); Uncertainty costs (UCT); Personal innovativeness in the domain of IT (PIT) (control variable).

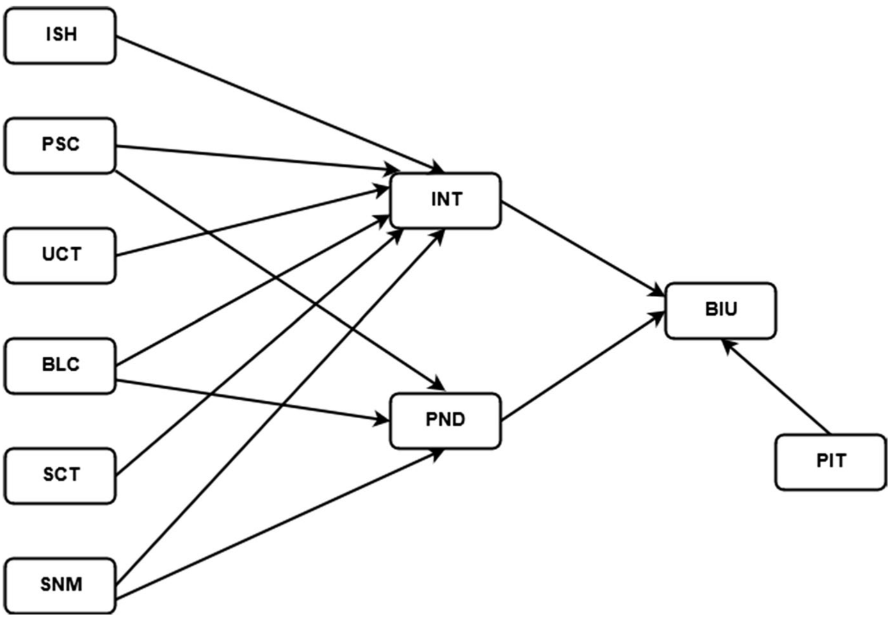

Fig. 1 Research model

4 Method

4.1 Research context

The present study was conducted in the Computer Science department at southwestern primarily 4-year university in North America where educational institutions have been encouraged to adopt open-source materials to save money for students through funding for curriculum development. The Department of Higher Education in the state to which the university belongs to has awarded more than $2 million from individual faculty initiatives to institutional and inter-institutional projects during the three-year period from 2018 to 2021. The goal of the state is to lead the way in Open Education Resources (OER) adoption to foster innovation, reduce costs and boost equity and overall student success. Some faculty of the university have applied and successfully received grants to produce and/or adopt OER in their classrooms from various programs including Arts to Business and Computer Science. The Computer Science department had one dedicated Linux course called Unix OS and two security courses that primarily used Linux OS as the platform for learning ethical hacking, network and application security. The Computer Science program makes use of open-source tools, technologies, and teaching materials as much as possible in many of its course offerings from CS1 foundational Computer Science course to the capstone Software Engineering.

4.2 Participants and procedure

Participants for this study were recruited through instructor announcements and emails. The survey was distributed mostly via class email list. Out of five courses selected, 3 courses used Linux OS as the primary operating system and 2 courses used Windows. There were roughly 25 students per course on average with the total population of about 125 students. Students were reminded of the survey in the class via quick announcements describing the purpose of the study, its impact and the nature of the collection of the responses as completely anonymous and voluntary. 82 participants voluntarily agreed to participate in the research study. The convenience sample included 16 females, 66 males; participants had a mean age of 23.04 years ($SD = 5.39$). Students completed an online survey over the course of the Winter 2019 semester. No response or participant was rejected.

4.3 Measures

Participants were asked to complete a self-report questionnaire. All items were scored on a 7-point Likert-type rating scale (1 = *strongly disagree* to 7 = *strongly agree*). Participants responded to statements related to the study measures adapted from Wang, Wang, and Lin's (2018) study: behavioral intention (BIU); Inertia (INT); Perceived need (PND); Benefit loss costs (BLC); Incumbent system habit (ISH); Procedural switching costs (PSC); Sunk costs (SCT); Social norms (SNM); Uncertainty costs (UCT); Personal innovativeness in the domain of IT (PIT) (control variable).

5 Analysis and results

To test the relationships between the constructs in the research model we used the partial least squares structural equation modeling (PLS-SEM; Henseler et al., 2016) approach. This study conducted data analyses using the WarpPLS software (Kock, 2017). The data analysis followed a two-stage strategy: first, we assessed the measurement model followed by an evaluation of the structural model.

5.1 Measurement model

We followed the measurement model evaluation guidelines suggested in the literature (Henseler et al., 2016; Kock, 2018). The overall model fit was assessed using the model fit statistics presented in Table 1; the results of these fit statistics met the recommended criteria (Kock, 2018).

In Table 2, we examined the item loadings, composite reliability coefficients, and the average variance extracted (AVE) to assess the constructs using the guidelines offered in the literature (Henseler et al., 2016; Kock, 2018). Item reliability was established as the factor loadings exceeded the cut-off value of 0.70. Composite reliability coefficients of the measures also exceeded the cut-off value of value of 0.70. Convergent validity of the constructs was confirmed as all average variance extracted (AVE) values exceeded the recommended cut-off value of 0.50.

With regard to discriminant validity, we used the Fornell-Larcker criterion (Fornell & Larcker, 1981) to confirm discriminant validity. As seen in Table 3, all the diagonal values are greater than the off-diagonal numbers in the corresponding rows and columns, thus supporting the discriminant validity of the measures.

Overall, the measurement properties of the measures were acceptable. We next proceed to the second stage: structural model evaluation.

Table 1 Model fit statistics

Measure	Values	Recommended Criterion
Average path coefficient (APC)	0.234, $p = 0.006$	Acceptable if $p < 0.05$
Average R-squared (ARS)	0.404, $p < 0.001$	Acceptable if $p < 0.05$
Average adjusted R-squared (AARS)	0.373, $p < 0.001$	Acceptable if $p < 0.05$
Average block VIF (AVIF)	1.598	Acceptable if <=5
Average full collinearity VIF (AFVIF)	2.177	Acceptable if <=5

Table 2 Measurement scale characteristics

Construct	Items	Loadings	Composite reliability (CR) coefficients	Average variance extracted (AVE)
BIU	BIU1	0.986	0.985	0.971
	BIU2	0.986		
BLC	BLC2	0.921	0.918	0.848
	BLC3	0.921		
ISH	ISH1	0.719	0.912	0.723
	ISH2	0.930		
	ISH3	0.924		
	ISH4	0.811		
INT	INT4	0.900	0.952	0.869
	INT5	0.954		
	INT6	0.942		
PND	PND1	0.824	0.937	0.748
	PND2	0.812		
	PND3	0.882		
	PND4	0.912		
	PND6	0.890		
PSC	PSC1	0.886	0.897	0.744
	PSC2	0.803		
	PSC3	0.896		
SCT1	SCT1	0.965	0.979	0.941
	SCT2	0.973		
	SCT3	0.971		
SNM	SNM1	0.952	0.951	0.907
	SNM2	0.952		
UCT	UCT1	0.829	0.889	0.727
	UCT2	0.864		
	UCT3	0.864		
PIT	PIT1	0.809	0.896	0.742
	PIT3	0.855		
	PIT13	0.916		

5.2 Structural model

In the second stage, the relationships between the constructs in the research model were ascertained by evaluating the structural model. All VIF values were below the suggested threshold of 5 (Kock, 2018), indicating that there were no multicollinearity issues. In addition, there was an acceptable level of predictive relevance as Q^2 coefficient values were greater than zero (Kock, 2018).

Table 3 Discriminant validity test

	BIU	BLC	ISH	INT	PND	PSC	SCT	SNM	UCT	PIT
BIU	**0.986**	−0.182	−0.111	−0.432	0.770	−0.246	0.107	0.441	−0.260	0.390
BLC	−0.182	**0.921**	0.289	0.221	−0.111	0.562	0.302	−0.034	0.490	0.027
ISH	−0.111	0.289	**0.850**	0.264	−0.286	0.486	0.084	−0.108	0.404	−0.026
INT	−0.432	0.221	0.264	**0.932**	−0.359	0.317	0.213	−0.073	0.455	−0.150
PND	0.770	−0.111	−0.286	−0.359	**0.865**	−0.265	0.213	0.553	−0.306	0.465
PSC	−0.246	0.562	0.486	0.317	−0.265	**0.863**	0.235	0.056	0.725	−0.239
SCT	0.107	0.302	0.084	0.213	0.213	0.235	**0.970**	0.398	0.341	0.249
SNM	0.441	−0.034	−0.108	−0.073	0.553	0.056	0.398	**0.952**	0.065	0.264
UCT	−0.260	0.490	0.404	0.455	−0.306	0.725	0.341	0.065	**0.852**	−0.238
PIT	0.390	0.027	−0.026	−0.150	0.465	−0.239	0.249	0.264	−0.238	**0.861**

Square roots of average variances extracted (AVEs) on diagonal

Table 4 Hypothesis testing

Path	Path	Path coefficient (β)	*p value*	Effect size (f^2)	Result
H1	INT→BIU	−0.141	$p=0.093$	0.064	Not Supported
H2	PND→BIU	0.691	$p<0.001$	0.537	Supported
H3	BLC→INT	−0.021	$p=0.425$	0.006	Not Supported
H4	ISH→INT	0.197	$p=0.031$	0.060	Supported
H5	PSC→INT	0.175	$p=0.049$	0.056	Supported
H6	SCT→INT	0.132	$p=0.108$	0.034	Not Supported
H7	SNM→INT	−0.011	$p=0.462$	0.002	Not supported
H8	UCT→INT	0.451	$p<0.001$	0.211	Supported
H9	BLC→PND	0.287	$p=0.003$	0.116	Not Supported
H10	PSC→PND	−0.139	$p=0.096$	0.052	Not Supported
H11	SNM→PND	0.508	$p<0.001$	0.297	Supported

The structural model results are presented in Table 4. We followed the guidelines for structural model testing in WarpPLS (Kock, 2018) and evaluated the path coefficients (β) and path significance (p value), including effect sizes (f^2).

6 Discussion

Our study examined a technology upgrade model of user intentions to switch to Linux. Using a dual process model of the antecedent factors influence on Inertia (INT) and Perceived Need (PND) on Behavioral Intention (BIU), we explored the influence of the following antecedent factors: Benefit loss costs (BLC); Incumbent system habit (ISH); Procedural switching costs (PSC); Sunk costs (SCT); Social norms (SNM); Uncertainty costs (UCT). The strongest relationship was the significant positive path between Perceived Need and Behavioral Intention ($\beta=0.691$,

$p<0.001$, $f^2=0.537$) followed by Social Norms on Perceived Need ($\beta=0.508$, $p<0.001$, $f^2=0.297$) and Uncertainty Costs on Inertia ($\beta=0.451$, $p<0.001$, $f^2=0.211$), with small effects from Incumbent System Habit and Perceived Switching Cost on Inertia as well. Only five out of eleven hypothesized path relationships were significant. Such a low number is surprising because the factors appear closely related on a conceptual level. However, we do note a pattern of influences. Whereas many relationships were not found significant, no factors were without relationship to another factor save Benefit Loss Cost, which is perhaps explained by its close relationship to Procedural Switching Costs. Overall, we find that the results support the effects of inertia and social norms on user switching intentions. However, we find the strongest path from Social Norms to Perceived Need to Behavioral Intention.

In the context of computer science students' intentions to switch to a Linux-based operating system, we find that the students felt compelled to switch to Linux, as represented by the strong link from Social Norm to Perceived Need to Behavioral Intention. However Social Norm does not explain all the variance in Perceived Need, as part of the variance can be explained as legitimate positive appraisals of the benefits to be derived by switching to Linux for students in computer science. Unfortunately, our model does not go further to characterize the formative factors of Social Norms. Thus, we argue that more attention needs to be paid to the construct of Social Norm as there are likely numerous antecedents related to socio-political notions, including group identification, group cohesion, and governance processes, in addition to notions of inertia, cost aversion, habits, and norms. At any rate, the link between Social Norm and Perceived Need in our study warrants further exploration.

Whereas Gong et al. (2020) found that inertia costs had a strong effect on behavioral intention in the context of payment systems, in our dual process model, we did not find a significant effect compared to Perceived Need. The difference being that switching to Linux is an end-user decision rather than a question of payment infrastructure. It is possible that ideological factors influence an individual's perceived need (Daniel et al., 2018). As recent history demonstrates, Linux adoption for municipalities is rife with politics and intrigue (Silic & Back, 2017). Technology switching intentions in the context of open-source software are undeniably political, which explains the strong relationships between Social Norm, Perceived Need, and Behavioral Intention in the context of a department-wide policy for promoting open-source software.

6.1 Implications

For computer science departments considering how to approach open-source in the courses, in addition to influencing social norms, they might also address the productive chaos (Kuwabara, 2000) of the bazaar model of free and open-source software development compared to the conventional cathedral model of over-engineered commercial applications. Open-source software has super-powered research (van Krogh & Spaeth, 2007) through multiplicative effects of sharing data and tools openly. Open-source movement can similarly boost computer science students' professional and technical skills. Organizations wanting to make the switch would do well to heed the experience (Silic & Back, 2017) of the Munich municipal government switch to Linux based environment and tools and provide the training and support necessary for a successful transition.

6.2 Limitations and future directions

This exploratory cross-sectional research is limited by its design. It uses a convenience sample and a single institution at a single time point. The model is parsimonious and does not account for all sources of variance in individual attitude formation and intentional behavior nor all relationships between the factors. The present study found support for Inertia and Social Norm on users' switching intentions. Our model suggests that user decisions are more influenced by social norms than by inertial factors in explaining user switching intentions for Linux. Future research should employ more qualitative methodologies like grounded theory and phenomenography to capture respondents' beliefs about technology and better inform their understanding of the determinants of technology switching behavior to design ecologically valid models of user switching intentions that account for social influence processes.

Whereas the literature on technology switching intentions recognizes powerful social and institutional influences on individual behaviors (Wang et al., 2018), the literature still evinces a cognitive bias as these influences result primarily from conscious appraisals. Rational choice theories are circumscribed by the very notion of intentional action. It bears mentioning that such theories will be less sensitive to other vectors of information that guide individual behaviors in the social realm, from the semiotic, political, cultural, historical, and social-affective dimensions which do not necessarily readily submit to rational appraisals. This might make them appear less important on the surface when accounting for individual behaviors, yet they cannot be discounted as sources of information informing intentional action. We know today that individuals are susceptible to a wide range of biases in judgements under uncertain conditions (Tversky & Kahneman, 1974) and there is a documented disparity between user behavioral intentions and actions (Ajzen & Fishbein, 2005). We also recognize the importance of the affective dimension in human behavior (Stasser & Dietz-Uhler, 2001) and the underlying political (social) dimension of individual decision-making. We are confronted by the contradictions of rational choice theory, namely that individuals are freely acting rational agents. Yet history and contemporary society consistently put the lie to these assumptions. Irrational behaviors in the light of socio-economic (i.e., political) considerations may be understood as the most reasonable course of action (Reicher, 2008).

7 Conclusion

In light of the open source movement, it is important to understand what might influence user technology switching intentions. The present study specifically examined user intentions to switch to a Linux-based open-source operating system. Overall, we find effects of inertia and social norms on user switching intentions. The present study has implications for improving education by fostering the employment of open source software as a strategy towards more equitable access to engineering education worldwide.

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Authors and Affiliations

David John Lemay[1] · **Ram B. Basnet**[2] · **Tenzin Doleck**[3]

David John Lemay
david.lemay@mail.mcgill.ca

Ram B. Basnet
rbasnet@coloradomesa.edu

1 McGill University, Montreal, Canada

2 Colorado Mesa University, Grand Junction, CO, USA

3 Simon Fraser University, Burnaby, Canada