Exploring the influence of ubiquitous workplaces on individual learning

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***Abstract*— Nowadays, the professional use of ubiquitous computing devices for data transfer and communication is becoming increasingly important. Workers become constantly connected and available. Moreover, they are constantly asked to be accessible. Falling in line with the abductive approach, this study has developed a model to investigate mobile and ubiquitous work consequences on user's learning. The theoretical framework for understanding learning is based on connectivism theory, as a learning theory for the digital age. An adapted survey was administered to 214 managers operating in IT and Telecoms sectors. Results show that social interactions generate an overload by providing redundant and useless information. Consequently, and contrary to what was said in previous researches, social interactions are an ongoing problem that can affect learning by enhancing the information load. This empirical evidence makes a valuable contribution for both managers and organizations. Future researches must include other workers categories and offer possible countermeasures.**

Key words: Mobile work, information overload, social interactions, individual learning

I. Introduction

Technological advancement and the promised rewards of mobile working have led to an explosion in mobile computing and telecommunications technologies in recent years [1]. Thanks to their unique characteristics, mobile devices facilitate value creation anywhere anytime. Although new forms of flexible works have emerged, we will interest on mobile work_as one of teleworking form_which is increasingly observed and practiced in business. It consists on activities leading mobile operator to perform his job, in whole or in part, outside the company, using mobile devices. While benefits are always expected [2], [3], we consider that it is interesting to enrich debates conducted around mobile work through studying its effect on individual learning.

Mobile work is not only a remote work mode, more important, it also generates mobilization of human interaction in the workplace in terms of spatiality, temporality and contextuality [4]. Learning is also a contextual activity since we can learn anywhere anytime [5]. The challenge for users is, therefore, to understand how best they might use mobile devices to support their learning. Whereas the literature is still unclear about mobile workers learning, this study will try to explore capabilities of mobile work to enhance or inhibit learning.

Our review of the literature reveals three major theories that provide an effect view of learning in many environments: behaviourism, cognitivism, and constructivism. Those theories fall short, however, when learning is considering as rich, informal, networked experience, whether in office, home, travelling or wandering. In this context, a blended approach to enabling learning with mobile technologies was necessary as successful and engaging activities draw on a number of different theories and practices [5].

With the changes that have occurred on learning possibilities, George Siemens has introduced the theory of learning called “connectivism” [6]. In this connectivist model, a learning community is described as a *node*, which is always part of a larger network. A network is comprised of two or more nodes linked in order to share resources. Nodes may have varied size and strength, depending on the concentration of information and the number of individuals who are navigating through the network [7]. In this way, "Know-how" and "know-what" are completed by "know-where" which refers to the question "where can we find the necessary information?" [8].

Two important elements are indispensable in understanding learning models in a digital era: Social network and information flow. In fact, new information is constantly being acquired through connection and interaction between nodes. Learning is thus becoming a process of connecting specialized nodes or information sources [6]. More important for this theory, that the ability to draw distinctions between important and unimportant information is vital. Consequently, connectivism stresses that two important skills that contribute to learning are the ability to seek out current information, and the ability to filter secondary and extraneous information [9].

While this conception is often associated with and proposes a perspective similar to Vygotsky's 'zone of proximal development' (ZPD) and Engeström's Activity theory (2001), we consider it as the most appropriate to approach the learning of mobile workers. In fact, as a result of the recent rapid advances made in information and communication technology, mobile work is consequently associated with an increasing amount of information [10] and with development of a large networks [1], [11].

In this context, it will be useful to enrich the current debates conducted around mobile work through the study of its consequences at the individual level. This paper investigates how mobile work could influence mobile worker's learning. The specific objective of this study is to verify the significant correlation, if any, exists among learning and its determining factors identified through our exploratory study. Data were collected through observations and semi-structured face-to-face interviews with Tunisian managers operating in IT and Telecoms sectors. This inductive phase helped us to understand human thoughts and actions in organizational context [12].

A total of 17 people participated in our exploratory study. Posts targeted were very active and dynamic requiring movement and a frequent use of mobile communication technologies. All those interviews were transcripted using qualitative coding. Two emerging codes were identified: information overload and social interactions are an ongoing problem that can affect mobile worker's learning.

This finding joins basic idea of cognitive load theory of Sweller (1988) [13]. According to this theory, cognitive capacity in working memory is limited, so that if a learning task requires too much capacity, learning will be hampered [14]. Nevertheless, cognitive load will not be considered in this research. We will limit our investigation to both concepts identified by our inductive research.

II. Conceptual Framework and Research Hypotheses

The proposed model is a predictive model of mobile's work consequences generated by our qualitative exploratory study "Fig. 1". In following sections, we will discuss hypothesis

A. Mobile worker's social interaction:

In this study, we focus on the structural dimension of social capital and more specifically social interactions of mobile workers. Social interactions promote access to different resources [15]. According to our interviews, the most important resource is informational. Information can be received anywhere anytime. Previous researches have highlighted that only information benefits have interested researchers [15], [16]. However, the information exchanged can also represent a risk factor. The 17 interviewers have considered social interactions as source of information overload. This consequence is a result of two phenomena as identified by our exploratory research: Too much solicitation and especially redundant and useless information received by different mobile devices.

Therefore deducing from the foregoing discussion, it is hypothesized that:

H1: *mobile worker's social interaction have a positive impact on information overload*

According to Vygotsky (1978), learning is a process of internalization. It is generated by interaction with the other in different contexts [17]. According to Chiu et al. (2006), social interaction between members of a virtual community is an effective way of sharing knowledge and learning [18]. The more these interactions exist, the more important the intensity, frequency, and the exchange of knowledge and skills [19]. We then propose that:

H2 : *mobile worker's social interaction have a positive impact on individual learning.*

B. Mobile worker's information overload:

Information overload has been exacerbated by the recent rapid advances made in information and communication technology [17]. The use of mobile technology is associated with an increasing amount of information at the user's disposal [20]. This phenomenon can be defined as a situation in which the amount of information an individual receives exceeds an individual's information processing capacity [21].

Our empirical investigation has showed that learning may be disturbed by an information overload. While we could not be able to identify a direct link between these two concepts, a moderation relationship was identified. For this study, the positive relationship demonstrated between social interaction and learning (*see H1*) can, beyond a certain threshold, impede learning. This threshold will depend on the level of the informational load, which is also caused by the social interaction. Indeed, as the information overlap with a phone that keeps ringing, emails to read and transmit, meetings and face to face conversations, interactions become threatening and also sources of redundancy. It will disturb operator promoting additional informational load. The operator will in this case adopt a partial review of his tasks. Therefore this study proposes that:

H3: *mobile worker's information overload moderates relation between social interactions and individual learning.*

Figure 1 presents the research model. The dependent variable is "individual learning" [IL] that can be influenced positively and directly by social interactions [SI], negatively and indirectly by information overload. The moderator variable information overload [IO] will alter the strength of the causal relationship. Although classically, moderation implies a weakening of a causal effect, a moderator can amplify or even reverse that effect [22]. Barron and Kenny (1986) assumed that the moderation can be captured by an XZ product term. For our case, moderation will be tested as IOxSI product term.

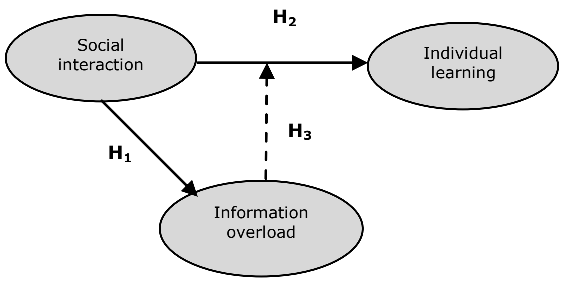

Fig1. Research model

III. Methodology

A random sample of 305 mobile middle or senior managers operating in IT and Telecoms sectors were selected. Survey questionnaires were mailed to them. A total of 214 responses were retained. All the respondents are males. The median age group of the respondent was that of less than 38 years (65.9%). About 81.4% of the respondents have university level of education. Consequently, results analysis will not be discussed according to gender, age and level of education as they can raise any interest in our case.

A. Measures:

All the scale items were measured on a five-point

TABLE I.

SCALE MEASUREMENT

Constructs	Items	Sources
Information overload	12	Scale construction
Social interaction	4	Chiu and al. (2006).
Individual learning	11	Haueter and (2003).

Likert-type scales that was anchored by 1= strongly disagree to 5= strongly agree to express the degree of agreement. The three constructs were modelled using reflective indicators. Scales are resumed in table I.

Research scales were operationalized on the basis of previous work and also newly designed. Some adaptations were essential in order to fit the current research context and purpose. “Social interactions” used a four-item scale measure of Chiu and al. (2006), “Individual learning” used eleven-item scale measure from Haueter and al. (2003) [23]. “Information overload” was measured by twelve items developed for this study.

New measure of IO was created by using a psychometric approach based on Churchill’s “scale development” procedure and on the C-OARSE method of Rossiter. While Churchill defines the construct in terms of the attribute only [24], C-OAR-SE construct definition requires specification of (1) the construct, (2) the object and (3) the attribute.

Three dimensions were retained. Informational one will be measured by five items, communicational one by three items and temporal dimension by four items.

B. Data analysis and measurement model:

To analyse both measurement and structural models, we used Smart PLS software for Structural Equation Modeling (SEM) technique [25] which can support at the same time exploratory and confirmatory research. It will be the appropriate software to this study since our model is a prediction of an impact not yet approved by researchers. It is also recommended for small sample size.

Construct reliability was assessed using Composite Reliabilities and Cronbach’s Alpha values. All these values were above 0.68 as recommended by Hulland [26]. We can then admit that the scales are reliable. Convergent validity was assessed using the average variance extracted (AVE) measure and Item loading values. According to Fornell and Lacker [27], Variance Extracted (AVE) by each construct should excee d the variance due to measurement error for that construct, i.e., AVE should be greater than 0.5. For our case, all the items loadings and AVE values are satisfactory and confirm the existence of convergent validity (see table II).

TABLE II.
CONSTRUCT RELIABILITY AND CONVERGENT VALIDITY

Research construct	Cronbach’s alpha And CR values	AVE value
SI	α= 0.825 CR=0.919	0,765
IO3*	-	-
IO2	α= 0.437 CR=0.780	0,616
IO1	α= 0.772 CR=0.869	0,683
ISxIO	α= 0.898 CR=0.952	0,906
IL	α= 0.969 CR=0.973	0,734

*mono-item construct after purification process

Furthermore, to evaluate discriminant validity, the AVE of each construct should be greater than the shared variance between the construct and the other model constructs [28]. In Table IV we can remark that the diagonal elements are greater than the off-diagonal elements in the corresponding rows and columns, therefore confirming that discriminant validity is verified (table III.).

TABLE III.

DISCRIMINANT VALIDITY

	SI	IO3	IO2	IO1		IL	AVE
SI	1						**0,765**
IO3	0,020	1					
IO2	0,001	0,074	1				**0,616**
IO1	0,024	0,242	0,400	1			**0,683**
ISxIO	0,001	0,004	0,042	0,057	1		**0,906**
IL	0,009	0,004	0,002	0,001	0,008	1	**0,734**

C. Structural Modeling Results:

The structural model was tested using the R^2. It is the amount of variance explained by independent variables. The R^2 values for the dependent variables – information overload (IO) and individual learning (IL) are respectively 0.213 and 0.17. According to our results, Information overload explains 21.3% of social interactions. Moderating variable explains 35.6% of individual learning while social interactions explain only 17 % of individual learning.

Based on R^2, the global goodness-of-fit (GoF) will be calculated. This value will assess the quality of the measurement and the structural models [29]. Our GoF is 0.721 which can be satisfactory (between 0.3 and 0.9). Thus, this study concludes that the research model provides an overall goodness of fit.

IV. Hypothesis tests and discussion of results

Table IV. summarizes the hypothesis tests.

The purpose of this study was to investigate and verify

TABLE IV.
HYPOTHESIS TEST

hypothesis	Path coefficient	Statistics	Results
H1: SI → IO	0.682	7.532	Supported
H2: SI → IL	0.359	5.621	Supported
H3: IOxSI →IL	0.532	3.394	Supported

the significant correlation between individual learning and two of its determining factors associated to mobile work. Hypothesis test showed that there is a significant and positive relationship between social interactions and information overload of mobile workers (t= 0.682, β = 7.532). A positive association exists between SI and IL. A significant and negative relationship was also founded between SIxIO and IL.

The findings have highlighted that social interactions influence positively the information overload of managers. While previous researchers have assumed that social interactions, as a structural dimension of social capital, generate benefits [15] [16], our results assume that social interactions is risk factor that can increase amount of information. Technological proximity is becoming a source of interruption and redundancy information.

Otherwise, in accordance with previous research, individual learning happens through social interaction. Based on our findings, information overload can moderate this positive effect. Our empirical investigation has showed that the more information overlap with mobile devices, the more interactions become threatening and sources of redundancy. Social interactions can thus disturb the operator by promoting additional informational load. Learning will consequently be disturbed.

V. Conclusion and Future research

Ubiquitous computing, through the social interaction that they mobilize, has been shown to be beneficial for learning. For this research, social interactions are source of overload and can disturb individual learning. An interesting area for future research is to examine other consequences of social interaction that can disturb learning (task interruption as an example). It will be then necessary for further research to verify the generalization of our findings in other sectors.

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