Take up my Tags: Exploring Benefits of Collaborative Learning in a Social Tagging Study at the Workplace

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Abstract. Meaning making is reflected in the reciprocal manipulation of artefacts mediating the shared meaning. We understand uptake, i.e. interaction with collaborators' interpretations of meaning, as one central mechanism and investigate its impact on individual and social workplace learning. Results of a social tagging field study (N = 17) indicate that uptake of others' tags leads to a higher shared understanding, but ambivalent effects on information search.

1 Introduction

Learning at the workplace by means of social technologies enables professionals to collaboratively solve emerging problems based on mediating artefacts [5]: e.g. a team receives a challenging project, for which its members explore supplementary resources, upload them annotated with tags and description and engage in a reciprocal annotation process until the problem is understood and an appropriate solution is found. The gathered resources in combination with the attached annotations represent mediating artefacts, which reflect the shared meaning negotiated in a collaborative knowledge building effort [8]. This negotiation process requires combining each other's knowledge or expertise, reciprocally: i.e. taking up the socially shared meaning and building on top of it by manipulating the mediating artefact, which leads to a composition of interrelated interpretations of meaning. This way, two workers, small groups or whole organizations are able to achieve more than alone [6].

The underlying mechanism, called meaning making (MM), represents the essence of collaboration [7]. MM stresses the interactive and reciprocal nature of negotiation processes and the fact that meaning resides in the social realm. It can manifest itself in manifold ways in sociotechnical systems ranging from more explicit forms of negotiation such as collaborative writing to more implicit forms such as social tagging. Recent empirical studies in CSCL confirm that collaboratively building shared meaning is an inherent and inseparable part of individual learning. For example, [3] find in their study of a group of university students using a social tagging environment that individual learning is dependent on collective processes in the group. In those groups where agreement was reached more quickly about the use of tags, individuals also learned better. [1] discover the dependency, as well, while studying navigation behaviour in a social tagging system based on coevolution's internalization and externalization processes. In particular, they figure out that collective knowledge reflected in the strength of associations in a tag cloud takes effect on navigation and results in incidental learning, i.e. a change of individual strength of associations in an internal test.

We hence assume that engagement in MM also leads to an internally shared understanding, i.e. an alignment of internally reached understanding [6], via internalization and externalization processes of coevolution. In this sense, collaborators, artefacts and interpretations coevolve in a constant dynamic process of MM, i.e. interpretations become manifest in artefacts, and artefacts in turn shape interpretations leading to a higher shared understanding and a more elaborated meaning in turn. A central concept in MM is uptake, a term used for interaction with interpretations of collaborators in terms of understanding and doing something further with them [8]: i.e. high uptake indicates engagement with the diverse accumulated meanings in a sociotechnical system and the respective social stimulation. In this way, high rates of uptake might yield benefits for individual and collaborative learning: on the social level (H1), uptake is expected to lead to a higher shared understanding of collaborators due to mutual adaptation; via social stimulation, uptake is expected to cue new ideas when exploring the Web, thereby, improving information search on the individual level (H2).

Empirical studies (e.g. [3] & [1] reported above) have shown collaborative learning influencing individual learning convincingly. However, these studies have not explored effects of social learning on shared understanding and have been mainly conducted in educational settings. There is less evidence about uptake effects in a workplace learning context, where learning typically happens autonomously at work and MM is embedded into current work activities Therefore, the purpose of the current paper is to explore effects of these uptake events on the individual and team in the working context. We therefore conducted a field study with a social tagging system at the workplace allowing for uptake via the interaction with others' tags in a tag cloud.

2 Method

To test the hypotheses, we carried out a social tagging study at the workplace lasting 4 weeks. Participants (N = 17) were recruited from Tallinn University, Graz University of Technology and Know Center: 4 were female and 13 male with an average age of 31.5 years (SD=5.5) and computer (n=11) or cognitive science (n=6) background.

In social tagging, uptake is reflected by the extent, to which a user reuses social tags, i.e. tags introduced by other users. Hence, uptake during exploration in the tag cloud was defined by the number of clicked, unique social tags. The task was to collaboratively explore web resources for the overall topic: 'Explore different digital, physical, and socio-political design ideas for a workspace that could enhance the exchange and creation of knowledge.' Participants were asked to consider others' contributions as cues to become aware of new perspectives of the topic and imagine writing a state of the art for a project proposal that points at different ideas (e.g. 'rotating desktop assignments') and sheds light on this topic from different perspectives. This task required to collect and tag 4 links or documents per week and to explore others' interpretations via a tag cloud in an online social knowledge repository called Know-

Brain [2]. When uploading, participants were prompted to select themes (sub-topics) from a multiple choice list derived from the exploration topic to enable the thematic classification of queries. The eight themes were ‘Gamification & Playfulness’, ‘Inspiration sources & techniques’, ‘Collaboration technologies’, ‘Personalization services’, ‘Augmented reality’, ‘Interior design’, ‘Wellbeing & health’, and ‘Socializing’.

All activities in KnowBrain were recorded in log files. To assess the internal knowledge, association tests (AT; word fluency) were applied including the eight search themes as stimuli and recorded in log files as well. To explore the benefits of uptake on the social level, i.e. higher shared understanding (H1), a median split with respect to uptake was applied to differentiate between participants reusing more or less unique social tags in the tag cloud (U_{high} vs. U_{low} group). Subsequently, we created a weighted graph, whereas the nodes correspond to the *n* participants and a tie was created between two nodes if they shared an association. The number of overlapping association between nodes is reflected in the tie strength (edge width). In other words, we created an $n \times n$ weighted adjacency matrix to visualize social networks that reflect the amount of shared understanding. Finally, we computed density and degree centrality of the networks. To explore the benefits of uptake on the individual level, i.e. more efficient information search (H2), search was characterized by the number of resources explored as well as search costs, i.e. the rate at which users explored new themes during their search. To quantify this rate, we extracted the corresponding sequence of collected resources for each user and determined for each position *i* (in the user’s resource sequence) the number of unique theme combinations n_i explored up to this point in time. After pooling these data from all participants, we then performed a regression of n_i on *i* and used the resulting slope *k* as an average estimate of the users’ search costs. Finally, the categorical predictor uptake (median split) was included to explore whether the rate of topic exploration is higher in the U_{high} than U_{low} group. At last, we correlated participants’ uptake in the tag cloud with the explored resources.

3 Results

3.1 Social Level - Shared Understanding

To exclude shared understanding between U_{high} and U_{low} group being pre-existing, we computed a comparison of means at t0 obtaining no significant difference: $t(13) = -0.09$, *n.s*. H1 assumes higher shared understanding in terms of the intersection of associations in ATs for the U_{high} than U_{low}-group. **Fig. 1** depicts the social networks of shared understanding. Visually analysing both networks, it seems that the network of the U_{high} group is more interconnected and includes on average stronger relations (more shared associations) pointing towards a higher shared understanding than the U_{low} network. Only outlier is Mary and Joseph’s relation with 12 shared associations.

SNA confirms the observed difference in interconnectivity and reveals a higher density for the network of the U_{high} ($D = 1.00$) than U_{low} group ($D = 0.89$): i.e. uptaker clicking on more unique social tags in the tag cloud have more edges to others (of all potential edges) due to their overlap in associations. As well, SNA confirms the difference in heavy weight edges and shows a higher score in the averaged node degree centrality (respecting edge count & weight) [4] for the U_{high} ($deg.$ = 14.95) than U_{low} group ($deg.$ = 11.72) network: i.e. uptaker clicking more unique social tags have more higher weighted edges due to on average greater overlaps in associations. A comparison of means validates the difference as tendentially significant: $U(15) = 56$, $p = <.10$.

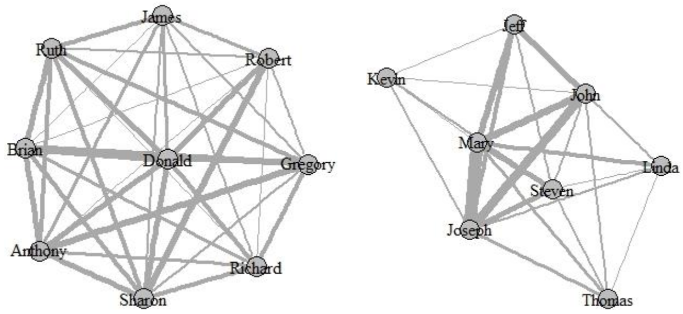

Fig. 1. Networks – U_{low} (left) & U_{high} (right). Edge width equals number of shared associations.

3.2 Individual Level - Information Search

H2 assumes more efficient information search in terms of more explored resources and lower search costs in the U_{high} than U_{low} group. We tested the assumption of lower search costs for U_{high} group by determining n_i, i.e. the number of unique theme combinations explored by a given user at a particular position i in her resource sequence. **Fig. 2** presents the average n_i for a sequence of i = 2 - 9 resources for both groups, reveals a linear relationship and – contrary to our expectation – a larger slope (lower search costs) for the U_{low} than U_{high} group. For instance, in order to explore four theme combinations, low versus high uptaker needed to collect about five and seven resources, respectively (U_{low}: $n_5 = 4.25$, $SD = 0.71$; U_{high}: $n_7 = 4.33$, $SD = 1.24$).

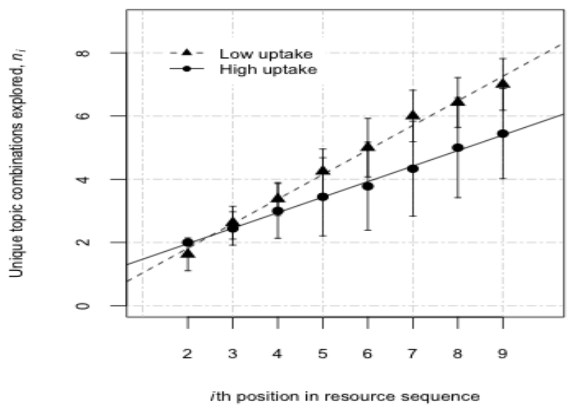

Fig. 2. Search Costs – average number of unique theme combinations n_i explored at a given position i in a resource sequence – for U_{low} & U_{high} group. *SD*s are indicated by error bars. Dashed and solid lines represent the linear regression of n_i on i for low and high uptaker.

To derive estimates of the varying search costs, we performed a linear regression of n_i on the two predictors i and *group* (U_{low} vs. U_{high}) summarized by **Table 1** and visualized by the dashed line (U_{low}) and solid line (U_{high}) in **Fig. 2**. In particular, we applied the following regression model: $n_i = \beta_0 + \alpha X_0 + \beta_1 i + \beta_2 X_0 i + \varepsilon$ (1), where X_0 takes on the values 0 and 1, if the corresponding resource was collected by a participant of the U_{low} and U_{high} group, respectively. The term $\beta_2 X_0 i$ represents the hypothesized interaction between the categorical predictor *group X* and the continuous predictor *i*. Thus, for resources of the U_{low} group, the intercept and slope is β_0 and β_1, respectively; for resources of the U_{high} group the intercept is $\beta_0 + \alpha$, and the slope is $\beta_1 + \beta_2$.

130 data points entered the linear regression[1], explaining about 70% of variance in the number of themes explored n_i (adjusted $R^2 = 0.69$, $p < .001$). It yielded a highly significant effect for the predictor i ($t = 8.60$, $p < .001$) and – in line with expectations – a highly significant interaction between this continuous and the categorical predictor *group* ($t = -0.30$, $p < .001$). However, contrary to our expectations, **Table 1** shows that the rate of theme exploration ('Slope') amounts to $\beta_1 = 1.09$ under the U_{low} condition, and declines to a rate of about 0.80 under the U_{high} condition.

Table 1. Summary of the regression of n_i on i and *group* (high vs. low uptake participants).

Group	Intercept	Slope
Low uptake	$\beta_0 = 0.53$	$\beta_1 = 1.09$
High uptake	$\beta_0 + \alpha = 1.00$	$\beta_1 + \beta_2 = 0.79$

Note. $\alpha = 0.47$; $\beta_2 = -0.30$

Moreover, more efficient search for U_{high} should also be reflected in the number of explored resources. We found a correlation between uptake and explored resources ($r_{spearman} = 0.51$(N = 17), $p < .05$): i.e. the more unique social tags are clicked in the tag cloud, the greater is the number of explored resources. To validate correlation results, we computed a comparison of means that resulted in an affirmative significant difference between U_{high} and U_{low} group as far as the exploration of resources is concerned: $M_{high} = 15.44$ (*SD* = 3.50), $M_{low} = 10.75$ (*SD* = 3.99), $t(14) = 2.56$, $p < .05$.

4 Discussion & Future Work

This social tagging study explored the social and individual effects of engagement in MM via uptake. While uptake seems to lead to a higher shared understanding of involved co-workers and more explored resources, it also results in higher search costs. It seems there is a complex trade-off of engagement in uptake and the respective social stimulation.

On the one hand, MM in a group of collaborators seems to lead to mutual adaptation over time and the production of more similar associations. An explanation could be that taking up tags of collaborators and receiving social stimulation results in irrita-

[1] Three user (N=17) collected not more than eight resources and one participant only six, resulting in 13(participants)*8(positions)+3(part.)* 7(pos.)+1(part.)*5(pos.)=130 data points.

tions and adaptations, so called accommodative processes [1]. They are element of internalization and externalization processes of coevolution and trigger the differentiation of underlying cognitive structures. Over time, these cognitive structures align which then leads to the establishment of shared understanding.

On the other hand, results indicate that uptake has an ambivalent effect on information search leading to more explored resources at the expense of higher search costs. This could be explained by the extent to which the search theme is narrow or broad. We assume social stimulation and the respective accommodative processes to trigger an elaboration of a narrow theme (or limited combination of themes) and the related cognitive structures, which becomes manifest in a large number of semantically similar resources: i.e. a small rate at which new themes are explored. Since search costs measure the broadness of search via the assessment of explored theme combinations over time, this kind of search behaviour yields worse results. Therefore, extensive uptake might have led to more explored resources, but to increased search costs.

In conclusion, the degree of engagement into MM or “trialogicality” [5] via uptake seems to represent a crucial determinant in individual and collaborative learning and the experience of respective effects. Future work will look at the role of assimilative processes during uptake, i.e. the repeated instantiation of existing cognitive structures, to better understand the effects of uptake onto the search costs. For example, each reused social tag could be weighted by the usage frequency to specify uptake and to enable a better prediction of the search focus based on the depth of elaboration of social cues. Shedding further light on MM and its underlying mechanisms will help to improve the design of collaborative working and learning systems as well as the structuring of pedagogical scenarios.

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