Take up My Tags: Exploring Benefits of Meaning Making in a Collaborative Learning Task at the Workplace

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Abstract. In the digital realm, meaning making is reflected in the reciprocal manipulation of mediating artefacts. We understand uptake, i.e. interaction with and understanding of others' artefact interpretations, as central mechanism and investigate its impact on individual and social learning at work. Results of our social tagging field study indicate that increased uptake of others' tags is related to a higher shared understanding of collaborators as well as narrower and more elaborative exploration in individual information search. We attribute the social and individual impact to accommodative processes in the high uptake condition.

Keywords: Collaborative learning · Meaning making · Uptake · Social tagging

1 Introduction

Leveraging social technologies at work enables professionals to collaboratively learn and solve ill-defined problems based on mediating artefacts [6] such as annotated resources: 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. These mediating artefacts reflect the shared meaning negotiated in a collaborative knowledge building effort [9]. Digital negotiation 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. This process leads to a composition of interrelated interpretations of meaning and enables two workers, small groups or whole organizations to achieve more than alone [7].

The underlying mechanism, called meaning making (MM), represents the essence of collaboration [8]. 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. In studying a group of university students using a social tagging system (STS), [3] found, for example, that individual

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learning is dependent on collective processes. Among groups, where agreement was reached more quickly about the use of tags, individuals also learned better. [1] discovered the dependency, as well, while studying navigation behaviour in a STS based on coevolution's internalization and externalization. In particular, they figured out that collective knowledge reflected in the strength of associations in a tag cloud takes effect on navigation and results in incidental learning in form of a change of the individual strength of associations in an internal test.

We, therefore, assume that engagement in MM also leads to an internally shared understanding of the collaborators, i.e. an alignment of their individual understanding [7]. Via those internalization and externalization processes, collaborators, artefacts and interpretations coevolve in a constant dynamic MM process: i.e. interpretations of collaborators become manifest in artefacts, which in turn shape their interpretations leading to a higher shared understanding of them and a more elaborated meaning. A central concept in MM is 'uptake', a term used for the interaction with others' interpretations in terms of understanding and doing something further with them [9]. High uptake indicates intensive engagement with the diverse accumulated meanings in a sociotechnical system and implies parallel social stimulation. This way, uptake suggests benefits for collaborative and individual learning: on social level (H1), uptake is expected to lead to a higher shared understanding of collaborators due to mutual stimulation; via this stimulation, uptake is expected to cue new ideas when exploring the Web, thereby, improving information search on individual level (H2).

Empirical studies (e.g. [3] & [1] reported above) have shown collaborative learning influencing individual learning convincingly. These studies, however, have not considered the extent of engagement with shared meaning and not explored effects on shared understanding. Besides, there is less evidence on benefits of MM in a workplace learning context, where learning is embedded into current work activities and typically happens in a self-regulated manner. Therefore, the purpose of the current paper is to explore effects of these uptake events on the individual and team in the working context. To test the hypotheses, we conducted a field study with a STS at the workplace allowing for uptake via the interaction with others' tags in a tag cloud.

2 Method

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 GmbH: 4 females and 13 males with an average age of 31.5 years (SD = 5.5) and computer (n = 11) or cognitive science (n = 6) background.

Professionals were asked to collaboratively explore web resources as basis for writing a state of the art for a project proposal about the topic *'Digital, Physical, and Socio-political Design Ideas to enhance the Exchange and Creation of Knowledge at Work.'* They were especially encouraged to explore different ideas (e.g. 'rotating desktop assignments') to shed light on the topic from different perspectives. They were also asked to consider others' contributions as cues to become aware of new perspectives. The task required to collect and tag 4 links or documents per week in a STS called

KnowBrain [2] and to explore other resource by means of a tag cloud. When adding resources to KnowBrain, participants were prompted to select themes (sub-topics derived from the exploration topic) from a multiple choice list to enable the thematic classification of the web queries before tagging them. The eight themes were 'Gamification & Playfulness', 'Inspiration Sources & Techniques', 'Collaboration Technologies', 'Personalization Services', 'Augmented Reality', 'Interior Design', 'Wellbeing & Health' and 'Socializing'.

We measured uptake by the extent to which a user reuses tags introduced by others, the 'social' tags. The number of clicked, unique social tags in the tag cloud, hence, defined the uptake rate. All activities in KnowBrain were recorded in log files. To assess the internal knowledge, we used association tests (AT; word fluency) [4] including the eight search themes as stimuli. To study benefits of uptake, 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} condition). For the exploration of benefits on social level, i.e. higher shared understanding (H1), the number of overlapping associations between the ATs was computed for both conditions. For the exploration of benefits on individual level, i.e. improved information search (H2), search was characterized by the number of explored re-sources and the rate at which users explored new themes during search (search costs).

3 Results

3.1 Social Level - Shared Understanding

H1 assumes higher shared understanding in terms of the intersection of associations in ATs for the U_{high} than the U_{low} condition. To exclude pre-existing differences between both conditions, we computed a comparison of means at t_0 obtaining no difference: $t(13) = -0.09$, *n.s.* To understand differences at t_1, a weighted graph was created, 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. 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.

Figure 1 depicts both social networks of shared understanding. Visually analysing them, it seems that the U_{high} compared to the U_{low} network is more interconnected and includes stronger relations (more shared associations) pointing towards a higher shared understanding. Only outlier is Mary and Joseph's relation with 12 shared associations, which could be due to parallel offline-collaboration at work. SNA confirms the observed difference in interconnectivity and reveals a higher density for the U_{high} ($D = 1.00$) than the U_{low} ($D = 0.89$) network: i.e. participants clicking on more unique social tags in the tag cloud have more edges to others due to overlaps in their association tests. As well, there is a difference in heavy weight edges reflected in a higher averaged node degree centrality (respecting edge count & weight) [5] for the U_{high} (*deg.* = 14.95) than the U_{low}

(*deg.* = 11.72) network: i.e. U_{high} participants have more higher weighted edges due to more overlapping associations. A comparison of means validates the difference as tendentially significant: $U(15) = 56, p = <.10$.

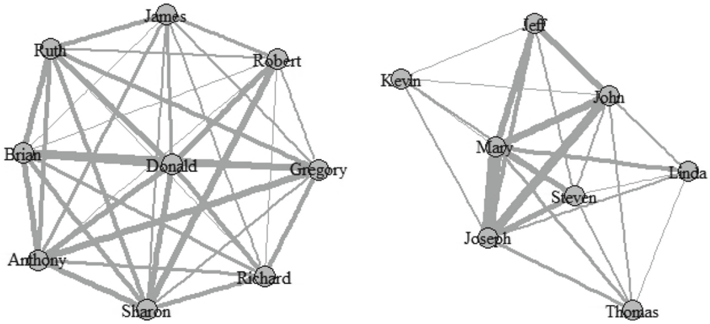

Fig. 1. U_{high} (left) & U_{low} (right) networks. Edge width is number of shared associations in AT.

3.2 Individual Level - Information Search

H2 assumes improved information search in terms of more explored resources and a faster exploration of themes during search in the U_{high} condition. To quantify the latter search costs, we extracted the sequence of collected resources for each user and determined for each position *i* in her resource sequence the number of unique theme combinations n_i explored up to this point in time. Afterwards, we performed a regression of n_i on *i* and used the resulting slope *k* as an average estimate of the users' rate of theme exploration. Finally, the categorical predictor uptake was included to explore whether the theme exploration is faster in the U_{high} than the U_{low} condition.

Figure 2 presents the average n_i for a sequence of $i = 2–9$ resources for both conditions. Contrary to our expectation, it reveals a linear relationship with a larger slope (lower search costs) for the U_{low} condition. For instance, in order to explore four theme combinations, U_{low} participants needed to collect about 5 resources, while U_{high} participants needed to collect about 7 (U_{low}: $n_5 = 4.25$, $SD = 0.71$; U_{high}: $n_7 = 4.33$, $SD = 1.24$). To derive estimates of the varying search costs, we performed a linear regression of n_i on the two predictors *i* and *condition* (U_{low} vs. U_{high}). 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 or 1, if the corresponding resource was collected by a participant of the U_{low} or the U_{high} condition. 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 $\beta_2 X_0 i$ between this continuous and the categorical predictor *condition* ($t = -0.30$, $p < .001$). However, contrary to our

[1] Three participants (N = 17) collected not more than 8 resources and one only 6, resulting in 13(users) * 8(positions) + 3(users) * 7(positions) + 1(users) * 5(positions) = 130 data points.

expectations, the rate of theme exploration (slope) amounts to $\beta_1 = 1.09$ under the U_{low} condition (intercept: $ß_0 = 0.53$), and declines to a rate of $\beta_1 + \beta_2 = 0.79$ under the U_{high} condition ($\alpha = 0.47$; $\beta_2 = -0.30$; intercept: $ß_0 + \alpha = 1.00$).

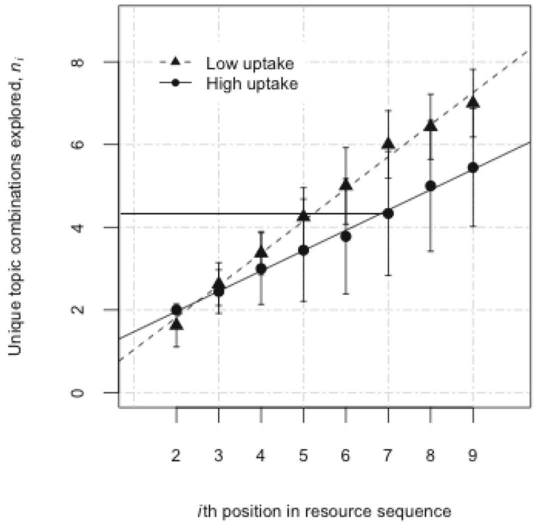

Fig. 2. Search Costs – average number of unique theme combinations n_i explored at a given position i in a resource sequence. *SD*s are indicated by error bars. A dashed and a solid line represent the linear regression of n_i on i for participants of the U_{low} and the U_{high} condition.

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} condition 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 benefits of engagement in MM based on uptake. High uptake of others' tags had a twofold effect: 1. Increase of shared understanding indicated by higher overlaps in collaborator's conceptual knowledge in ATs & 2. Narrower and more elaborative search indicated by a slower theme exploration with more considered resources. On the one hand, uptake seems to lead to a higher shared understanding of co-workers. Taking up others' tags and receiving parallel social stimulation could result in irritations and adaptations, called accommodative processes [1]. They specify internalization and externalization processes of coevolution and trigger the differentiation of underlying cognitive structures. Over time, these structures align establishing 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 respective accommodative processes to trigger an elaboration of a narrow theme (/limited theme combinations) 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 uptake or engagement in MM, the "trialogicality" [6], seems to play a crucial role for experiencing benefits in individual and collaborative learning. Future work will consider the thematic focus of uptake and the role of assimilative processes, i.e. the repeated instantiation of existing cognitive structures, to better understand the effects of uptake onto search costs. For example, each reused social tag could be categorized by topics and weighted by the usage frequency to infer on the depth of elaboration of search themes. Furthermore, we will qualitatively validate and deepen the assumptions on professionals' tagging behaviour. Shedding light on MM and its underlying mechanisms is going to improve the design of collaborative working and learning systems as well as the structuring of pedagogical and workplace scenarios.

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