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A COMPARISON BETWEEN INDIVIDUAL AND COLLECTIVE LEARNING IN DESIGN

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Abstract

In this paper, individual and collective learning are analysed and compared based upon an individual and a collective learning model in design [1]. Two experiments were performed and recorded to investigate individual and collective learning: the design process of an individual designer using the think aloud method; and, the recording of a meeting of a student design team. The protocol analysis approach was used in both experiments to analyse the data. This research provides a useful insight into individual and collective learning in design, which can serve as a basis to identify the similarities and the differences of the requirements for computer support for individual and collective learning.

Keywords: protocol analysis, design teams, human learning

1 Introduction

Learning is regarded as an important issue in the domain of Artificial Intelligence. A number of Machine Learning systems have been developed within the context of design (see review in [1] for more detail). However, it is identified that the understanding of phenomena of learning in design is very limited with the focus on development of computer tools to support learning in design [1] . As such, a model of learning in design is developed that describes what learning is, how and why learning occurs, and what the links between designing and learning are [1]. The model explains learning in design in the context of a *single* designer. Wu and Duffy argue that agents (i.e. designers or computers) could not only learn individually but also collectively through interactions in the context of team design, called *collective learning* [2]. A model of collective learning in design is proposed. In this paper, the similarities and the differences between individual and collective learning are further analysed.

Two experiments were undertaken to compare the two types of learning. In the first experiment, the design process of an individual designer was recorded during which the designer was asked to verbalise his thoughts regarding design decision-making. In the second experiment, the meeting of a design team was recorded. The protocol analysis approach was used in this research and applied to the transcribed tapes. Cross et al. [3] argued that protocol analysis has become "the most likely method (perhaps the only method) to bring out into the open somewhat mysterious cognitive abilities of designers". Protocol analysis has been widely used in investigating the cognitive behaviour in design [4-8]. The process of protocol analysis includes data segmentation, coding, analysis and interpretation [9]. One of the important issues in protocol analysis is the development of a coding scheme. For the same protocol data, there can be different results using different coding schemes. The coding schemes used in this investigation are described in [1, 2].

The objectives of this work are to provide an insightful understanding of individual and collective learning, and to provide a basis to identify the similarities and differences between the requirements for computer support for individual and collective learning in design. In the current research, there are a number of systems that support individual learning in design, however, only a very limited number relate to collective learning [10-12]. Understanding the phenomena of collective learning in design and comparing these two types of learning, can serve as a basis for the development of computer tools.

2 Experimental investigation

Two experiments were undertaken to compare individual learning and collective learning in design. The first experiment is adopted from [1], in which the design activities of one designer were recorded using a digital video camera. During the design process, the designer was asked to verbalise his thoughts whilst making design decisions. The designer has more than ten years experience in providing a consultancy service for the design and supervision of construction of high-speed naval crafts and warships. During the experiment, the designer was working on the general arrangement of a 60-metre offshore patrol vessel. The design session lasted 2 hours 45 minutes.

A meeting of a student design team was recorded within the second experiment. Within the meeting, the students were tasked with designing a fluid delivery system for a three dimensional printer. The meeting was again recorded using a video camera. During the meeting, the designers used pen and paper to sketch their design ideas. The sketches drawn by the designers were analysed and used to assist in understanding the verbal data. The team members are represented as G, P, M and D within the protocol analysis. The whole design session lasted 1 hour 13 minutes. During the recording process, the camera operator moved around and recorded both the overall view and the local view. The overall view captured the interaction of the designers, whereas the local view captured the gestures and sketching activities of individual designers.

3 An individual and collective learning model in design

Sim developed a model of learning in design - Figure 1 [1], which was evaluated using the first experiment. The model described "the what", "the how" and "the why" of learning in design in the context of a *single* designer.

Sim formalised the elements for a design and a learning activity. The elements for a design activity include *design goal*, *input knowledge* and *output knowledge*. The elements for a learning activity include *learning goal*, *input knowledge*, *output knowledge*, *learning trigger*, and *learning operator*. The learning operators transform input knowledge to output knowledge, which are derived from the work of Michalski [13]. The opposed pairs of learning operators in [1] are *generalisation/specialisation*, *abstraction/concretion*, *similisation/dissimilisation*, *association/disassociation*, *explanation/discovery*, *agglomeration/decomposition*, and *derivation/randomisation*. The elements for designing and learning are linked with each other, which have been identified as: teleological link, rational link, and epistemic link. A teleological link is related to the goals, i.e. a learning goal can precede a design goal, or a design goal can precede a learning goal. A rational link represents the reasons that trigger learning, whereas an epistemic link is concerned with knowledge change during a design process.

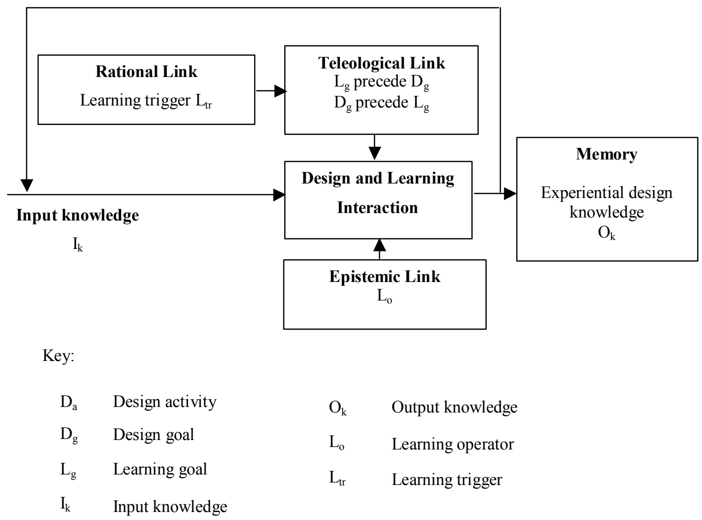


Figure 1 An evolved model of learning in design, Model-LinD (adapted from [1])

Wu and Duffy have extended Sim's work through the investigation of collective learning in design [2]. A model of collective learning in design was proposed based upon the existing learning theories and models, and investigated using protocol analysis within the second experiment - Figure 2. Collective learning exists in team design [2]. Similar to individual learning, collective learning elements are identified as input knowledge, output knowledge, collective learning goal, learning operators, and learning triggers. Three types of links between team design and collective learning (i.e. epistemic link, teleological link, and rational link) are also identified. What is learned is stored in *Collective Memory*, which can be used for current or future design practice and is defined as the sum of individual memories and shared memories. Individual memories can be the memories of individual designers or computers. Shared memories can be the design documents, drawings, etc, shared by team members. In the next section, the similarities and differences between the two types of learning are further analysed with the focus on 'the what' (i.e. input and output knowledge, and the type of learned knowledge), 'the why' (i.e. the learning triggers) and 'the how' (i.e. learning operators).

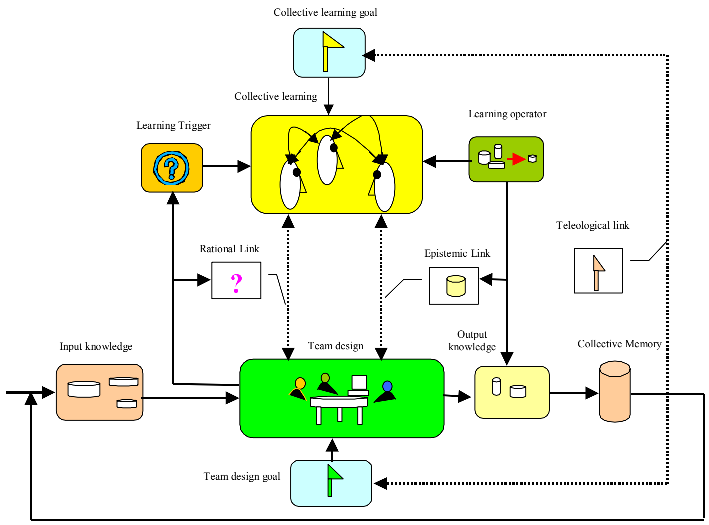


Figure 2 A model of collective learning in design (adapted from [2])

4 Analysis results

4.1 Input and output knowledge

In individual learning, an agent carries out learning activities without interactions and sharing information with other agents, although an agent can learn based upon multiple knowledge sources. What is learned is stored in individual memory. However, in the context of collective learning, the learning process becomes more complicated in which agents can share their knowledge and collaborate in the learning process. Five modes of input knowledge in collective learning are identified: *One-To-One*, *Many-To-One*, *One-To-Many*, *Many-To-One-Plus-Itself*, and *Combination of the modes* – Figure 3. One agent can either acquire knowledge from another, or from many other agents. Likewise, one agent can provide input knowledge for many other agents to learn. Also, one agent can learn based upon a combination of many other agents' input and its own knowledge. The fifth mode represents the possible combinations of the other four modes. For example, one agent can acquire a piece of knowledge from another agent and provide that knowledge as input knowledge for many other agents' learning activities.

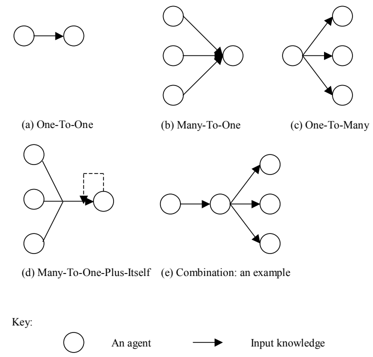


Figure 3 Modes of input knowledge

These five modes of input knowledge have been observed within the experiments - Table 1. The italic words within the protocol are key words or sentences used to identify collective learning activities and modes of input knowledge. In the first protocol, M learned from G that the cartridge should not be sealed. In the second protocol, G learned from M and P how the flow could be controlled. In the third protocol, the rest of the team members learned from G that they have to use a cartridge. In the fourth protocol, G learned that the cartridge has to be sealed based on the input knowledge from D and P and her own knowledge. In the fifth protocol, M learned from P and shared that knowledge with D.

4.2 Types of Learned knowledge

Sim classified the knowledge that can be learned individually as [1]: product design knowledge and design process knowledge. Product design knowledge includes: *knowledge of design decomposition*; *empirical knowledge of quantitative and qualitative relationships*; *knowledge of design constraints and design expectation*; *knowledge of design performance evaluation*; and, *knowledge of product function and the causal model*. Design process knowledge includes: *knowledge of design plans*; *knowledge of case dependent design plans*; and, *knowledge of generalised design plans*. It is suggested that these types of knowledge can also be learned collectively through interactions between agents. For example, one agent can acquire a piece of design decomposition knowledge from another agent.

Besides the knowledge that can be learned individually, there are other types of knowledge that may only be learned through collective learning:

- *Knowledge of agents' interactions*. Agents can learn how different agents interact and co-ordinate with each other.
- *Common knowledge*. When all the agents in a team learn the same piece of knowledge, that knowledge is considered as common knowledge. The third protocol in Table 1 shows an example of common knowledge. With the protocol and the design activities of later stages, it shows that all the team members learned the same piece of knowledge that they are going to use a cartridge.
- *Meta-knowledge*. Meta-knowledge is the knowledge of knowledge. Examples of meta-knowledge can be the knowledge of how agents solve the design problem or the knowledge of which agents own what kind of knowledge. Table 2 depicts an example of meta-knowledge learning, in which the team members learned that M knows the maximum volume of the flow.

Table 1 Observed modes of input knowledge

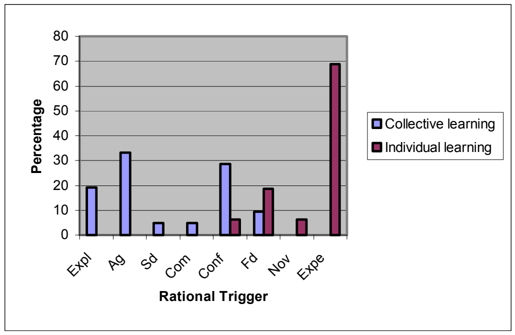
No.	Protocol Data Segmentation	Modes of Input Knowledge
1	M: *Was it sealed though?* G: *No*... which was part of it but even then it shouldn't, because it was totally pouring out like. M: *But even* it was sealed. It is probably put too much pressure on the thing. Because it was totally flooding out at the rate at just come out normally	One-To-One
2	G: *Is there anyway that we can incorporate the valve that operate and that is also run by the processor in the computer?* So that when that is reaching out it allow the flow to reach in. G: *Is there any other way to do it when it is being controlled?* M: *Just put valve on it or something*. P: *You can control the reservoir as it is we talk about having an injection system* rather have a valve on it, having a controller and the plunger to have a certain amount coming out at one time. G: You *are not control* the level at the cartridge. P: That will control the amount that was getting leak out, if it is pressurised. G: *Like at the top in the tank*? P: *Yeah*.	Many-To-One
3	G: Right, we have to use cartridge because we are using the cradle. *Because Gerry said so*. So we have to design a little bit to go on the top of this about this topic. D: *Yeah*. It is not just the tube into the ink recess or whatever it is called. M: *Yeah*.	One-To-Many
4	G: *That doesn't have to be sealed (pointing to drawing) because as long as that water level's there you're not gonna get any water in it.* They're not gonna get any air in it rather. As long as it's down to like there, know what I mean, as long as that bit's covered. D: *Even there*, if it's running through a sponge then you're not gonna get any air through it anyway. P: *Don't want* it contaminated with dust as well, you know you want to keep it quite... G: *Aye, it would definitely have to be a sealed ...*	Many-To-One-Plus-Itself
5	D: I think we're talking about size here, we're all talking about … what about (drawing and describing) still have the same volume. What's gonna give you more stability? M: *Why don't we just make something that you can stick anywhere and have it, like, detachable, like Paul was saying*?	Combination: One-To-One-To-One

Table 2 An example of meta-knowledge learning

G: *Gerry told us what the maximum volume was for that kind of build*. M: *I have it (looking for the folder)*.

4.3 Learning trigger

Individual learning can be driven by: *novelty; conflict; failure;* and, *expedience* [1]. The rational triggers for collective learning have been identified as: *explanation*; *agreement; conflicts; success or failure of a design;* and, *complement design ideas* [2]. Learning triggers are not identified in all of the learning activities. Designers can learn a piece of knowledge from other agents without any reason. Figure 4 illustrates the distributions of learning triggers in individual and collective learning within the two experiments. It would appear that most of the individual learning activities were triggered by expedience and failure of a design, while most of collective learning activities were triggered by agreement, conflict or explanation of design rationale between different agents. This suggests that agreement; conflict and explanation triggers occur more commonly in team design and thus result in collective learning.

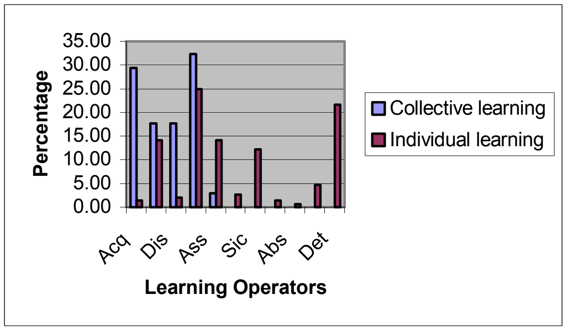


Key: Expl-Explanation; Ag-Agreement; Sd-Success of design; Com-Complement of design ideas; Conf-Conflict; Nov-Novelty; Expe-Expedience.

Figure 4 Distribution of learning triggers in individual learning and collective learning.

4.4 Learning operator

Learning operators in collective learning link input knowledge and output knowledge between different agents. The learning operators identified by Michalski [13] are used as a basis in both individual and collective learning. The learning operators identified in individual learning in the first experiment include *acquisition*, *explanation*, *discovery*, *derivation*, *association*, *decomposition*, *similarity comparison*, *generation*, *abstraction*, *specification* and *detailing*. The learning operators identified in the second experiment are *acquisition*, *explanation*, *discovery*, *derivation* and *association*. The distributions of the learning operators in both types of learning are illustrated in Figure 5. Acquisition has a high percentage in collective learning, approximately 30%, whilst the operator is negligible in individual learning. This may be due to it being easier for an agent when working in a team to acquire knowledge from the other agents. Discovery has high percentage in collective learning, approximately 18%, whilst again being negligible in individual learning. Team design may more easily promote discovery and thus result in collective learning, which is consistent with the synergy view of the efficiency of team-working [14, 15]. Association has a relatively high percentage in individual learning, approximately 15% whilst there is low percentage in collective learning, around 3%. This would imply that one agent in isolated design may more easily associate knowledge sources and produce new knowledge than in team design. Derivation has the highest percentage in both collective learning and individual learning. It suggests that agents tend to derive new knowledge from existing knowledge whether working alone or in a team. Explanation has a relatively high percentage in both types of learning. The learning operators, including decomposition, similarity comparison, generation, abstraction, specification, and detailing, are not identified in the collective learning experiment while they are identified in the individual learning experiment.



Key: Acq-Acquisition; Expl-Explanation; Dis-Discovery; Der-Derivation; Ass-Association; Dec-Decomposition; Sic-Similarity comparison; Gen-Generation; Abs-Abstraction; Spe-Specification; Det-Detailing

Figure 5 The distributions of learning operators in collective learning and individual learning

5 Discussion

It should be noticed that individual learning could also occur in team design, that is, agents not only learn collectively but also individually. Table 3 illustrates an example of individual learning in team design in which M learned individually by comparing the telephone cables with the tubes of the printers. The learned knowledge is that if the tubes of the printer are arranged like telephone cables they won't tangle up.

Table 3 An example of individual learning in team design

M: So that's *like why phone cables* are like that - so they don't tangle up. G: They can do themselves quite well. M: Aye, but not if it was like about that long (pointing to drawing).

In this paper, a comparison is made between individual learning and collective learning. The implications for computer supported collective learning in design is that it should include:

- Mechanisms for knowledge sharing. Interested agents can share both input and output knowledge. To achieve this, some communication mechanisms between agents are required.
- Learning operators. The learning operators can transform input knowledge into output knowledge and shall be equipped within agents. The existing machine learning methods (e.g. explanation-based learning) can be used as learning operators in an agent-based learning system.
- Learning triggers. Learning triggers (e.g. failure or success of a design) will trigger one or more agents to learn.
- Collective memory. Individual agents shall have their own memory for knowledge storage. Also, there shall be a common memory where all the agents can access to acquire knowledge and likewise agents can store their knowledge in the shared memory.

Protocol analysis has been used in this research. Protocol analysis is widely used to investigate the cognitive behaviour in design. However, it is also agreed that there are limitations in the protocol analysis approach. The main limitation lies in the subjective analysis of protocol data. In this research, for example, although key words, phrases, sentences and inference from the context of the design are used to identify the designing and learning elements, it was apparent that there are situations in which it was difficult to make a precise judgement. It is suggested that some other means can be used to assist the analysis.

For example, after the initial analysis, a structured questionnaire based upon the initial analysis can be carried out against the subjects of the experiment to justify the results.

6 Conclusion

In this paper, the similarities and differences between individual learning and collective leaning are analysed. It is suggested that designers learn during the design process, both in an isolated design context and in a team design context. Both individual learning activities and collective learning activities have similar elements: input knowledge, output knowledge, learning goals, learning triggers and learning operators. Three types of links between designing and learning exist in both types of learning, called epistemic link, rational link and teleological link. However, the differences between them, regarding to 'the what', 'the why' and 'the how', are identified as:

- Input knowledge and output knowledge. Differing from individual learning, collective learning can involve multiple knowledge inputs from different agents. Other agents can share what is learned. Five modes of input knowledge in collective learning are identified, called *One-To-One*, *Many-To-One*, *One-To-Many*, *Many-To-One-Plus-Itself*, and *Combination of the modes*.
- Types of learned knowledge. It is suggested that what is learned individually can also be learned collectively. However, there are types of knowledge that can only be learned through collective learning, which include knowledge of agents' interaction, common knowledge, and meta-knowledge.
- Learning triggers. There are learning triggers common to both individual learning and collective learning, which are conflicts and failure or success of a design. Learning triggers (e.g. explanation by agents, complement design ideas, agreements between agents) have been identified in collective learning but not in individual learning. Through the analysis, it seems that most of individual learning activities are triggered by expedience and failure of a design, while most of collective learning are triggered by agreement or conflict or explanation of design rationale between different agents.
- Learning operators. The learning operators produced by Michalski [13] can be applied to both individual learning and collective learning. Differing from individual learning, learning operators in collective learning link input knowledge and output knowledge between different agents. It is interesting that *acquisition* and *discovery* are more likely learning operators in collective learning than individual learning, while *association* is more likely in individual learning than in collective learning. However, *derivation* and *explanation* are apparent in both types of learning.

Based upon the comparison, implications for computer supported collective learning in design are derived. It suggested that requirements for computer supported collective learning in design would be different from those supporting individual learning, which will be detailed in future research.

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