# Chapter 6.26 Operational Knowledge Management

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#### INTRODUCTION

The differences between the paradigms of knowledge management (KM) and operations management are huge. Whereas KM is rooted in the disciplines of human relations, sociology, organization analysis, and strategic management, the operations management paradigm finds its roots in industrial engineering, business economics, and information systems. These differences result in poor acceptance of KM ideas in operations management and vice versa. Several approaches to this problem are possible. For instance, one may state that the operations management paradigm is irrelevant for knowledge management. This is incorrect, because besides of the traditional person-oriented knowledge management processes, modern knowledge intensive firms use reengineered knowledge processes intensively (e.g., Hansen, Nohria, & Tierney, 1999). An alternative approach may be to forget about the KM paradigm and only use the operations

management paradigm. This is wrong again, because most industrial enterprises compete on the development and exploitation of their expertise and human capabilities (Hamel & Prahalad, 1994; Quinn, 1992). Consequently, if knowledge management is relevant and if operations management is not irrelevant, then the main question is how to translate knowledge management issues into an operations management framework. I provide a conceptual framework for such a knowledge operations management (KOM) perspective.

## BACKGROUND

Operations management studies the handling or transformation of inputs to outputs (the operations function), and the consequent realization of organizational goals via certain means (management of operations) (Hill, 1983). Operations management thus distinguishes objects, which are the inputs and outputs of operations, related support tasks,

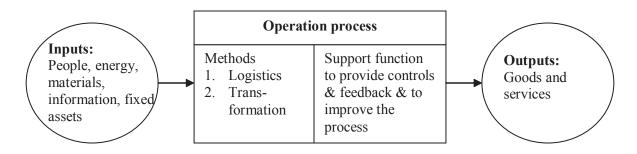


Figure 1. The operations function (based on Hill, 1983, p. 25)

and the setting of goals and application of means. In the operations, I distinguish logistics as the delivery of the input to a client without changing this input (Ballou, 1992) from transformation as the change of the input object to something different (see Figure 1).

Given the wide paradigmatic differences between operations management and KM, not many attempts have been made to apply operations management on KM. One of the scarce attempts is from Armistead (1999), who distinguishes knowledge inputs and outputs and four related operations processes, that is,. two transformation processes (knowledge creation and knowledge embedding) and two knowledge logistics or transfer processes (exchange of knowledgeable people and the exchange of knowledge representations). The KM literature sees knowledge creation and embedding as related organizational learning processes (Nonaka, 1994), therefore, the term learning better covers what we mean by knowledge transformation. Finally, Armistead also defines metrics to control and feedback to improve these processes. This article continues the attempt made by Armistead with a further specification of a knowledge operations management model. Such a model does not only structure the KM field, but at the end of the article I also will explain some of its heuristic value.

### MAIN FOCUS: THE KOM MODEL

In the context of KOM, the input-output objects are different types of knowledge. The input objects may be handled in operations without fundamentally changing them. This is what I call knowledge logistics and includes the storing and distributing of knowledge and its related representations. Alternatively, in learning processes, the knowledge inputs are transformed to new or different knowledge objects. The logistic process is an important support for learning, especially when done in organizations where learning is essentially a group process. Authors in the artificial intelligence discipline (e.g., Turban, Aronson, & Bolloju, 2001) have stated that besides people, machines also can learn. Although this is basically correct, the artificial intelligence field mainly regards learning at the behavioral and statistical level and not at the level of understanding and human skills formation, which is the focus of the KM literature. Thus, I exclude machine learning from KOM. In the knowledge operations management framework, the operation methods are supported by human and information technological means for specific goals, and metrics are used to control and deliver feedback on process performance as presented in Figure 2.

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