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Knowledge complementarity: Transforming buyer-seller relationships for synergistic effects

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ABSTRACT

In a turbulent market environment, creating innovative products that exceed customer expectations is a crucial priority for firms in a buyer-seller relationship. Often, the most expedient route for a firm is to seek to develop new competencies through a collaboration with another firm possessing complementing intellectual property (IP). Despite much research, the role of knowledge complementarity (KC) in buyer-seller relationships is still not well defined.

A new framework using absorptive capacity characterizes distinct types of KC and its effects on buyer-seller relationships. This initial research establishes a theoretical basis for later empirical work on buyer-seller relationships that generate new IP.

Key Words: Knowledge Sharing, Collaborative Partnerships, Absorptive Capacity, Technology Transfer, Inter-organizational Workflows, Knowledge Acquisition, Innovation Process

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Introduction

In a turbulent market environment, creating and delivering products and services that exceed customer expectations is a crucial priority for firms in a buyer-seller relationship. Often a firm may lack some, or most, of the requisite intellectual property (IP) to create or adapt products to rapidly emergent market requirements. Often, it is more expedient to exploit the knowledge resources of their partner firms (i.e. buyers, sellers and customers) through knowledge sharing rather than indigenously developing new IP on their own (Kim et al., 2012). Park & Hong (2016) present a case where two competitors collaborated to develop new technology for a low cost air conditioner for the China market at higher quality and low cost then either could have accomplished alone.

The presence of geographically-mediated complementary knowledge resources is beneficial to the innovative activities of small and large firms (Feldman, 1994). Internal R&D and external knowledge acquisition are complementary innovation activities (Cassiman and Veugelers, 2006). An effective knowledge management strategy requires a complementarity relationship which aims to achieve the synergistic effects of the tacit-internal-oriented and explicit-external-oriented innovative activities (Choi et al., 2008). Schoenherr et al. (2014.) found that tacit knowledge has a stronger influence on supply chain performance (in this work considered ease of new IP development through knowledge sharing).

However, the ability to absorb new knowledge from a partner firm will influence how responsive a firm is to developing innovative products and its performance (Dobrzykowski et al., 2015). Sudhindra et al. (2014) found that there are nine knowledge dimensions (i.e. purpose, tacitness, strategic value, shareability, and complexity, dependence on system, evidence, time, and measurability). The model developed in this research assumes that the knowledge objects are shareable, an inherent characteristic of complementary knowledge. Of course, the mechanism for sharing tacit knowledge will be very different from explicit knowledge however the now model is not effected by the modularity of knowledge exchange (e.g. EDI vs face-to-face, etc.) but rather only its effects on knowledge sharing and how it is influenced by knowledge complementarity (KC).

LITERATURE REVIEW

Knowledge complementarity (KC), as conceptualized in (Kim et al, 2012) and used in this work is the case when two disparate knowledge bases may be combined for super-additive value (more than the sum of its parts). One might consider the lay example of two people each knowing two different digits of a 4-digit combination lock. Together this knowledge is more useful than simply knowing two of the four numbers. Another example might be the complementarity of machine vision and artificial intelligence in the context of self-driving cars.

Current conceptualizations of KC capture higher order constructs such as the relatedness of product, managerial and customer knowledge (Tanriverdi & Venkatraman, 2005). However, to better understand how knowledge can be combined and its effect on buyer-seller collaboration we first need a more fundamental definition of knowledge complementarity. The following sections present how knowledge objects can be represented as vectors and characterizes KC using absorptive capacity as a conceptual basis.

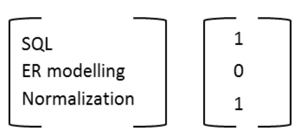
Literature Review of Knowledge as a Vector: Selected Works and an Example

Knowledge can be thought of as a set of elements that comprise intellectual capital. Each firm's knowledge stock can be represented as a vector with N binary elements (Cowan & Jonard, 2009). Mowery, Oxley, & Silverman (1996) represent two firm's knowledge as being similar by measuring the possession of elements of knowledge such as common patents or common citations to determine the extent to which the two firms' knowledge is similar.

Thus, let V_1 be the knowledge vector for firm 1 such that $V_1= \{v_i \mid v_i \in [0,1] \}$ and $i=\{0,1,\ldots N\}$ and similarly V_2 for firm 2. A value of 1 for an element v_i implies that the presence of competency (explicit or tacit) represented by that element is sufficient to be considered extant, usable and extensible. Likewise, a vector element of zero means that competency is insufficient to create a usable ability. Thus, each firm has knowledge stock that can be represented by a vector with N binary elements for both which will determine the presence or lack of KC.

As an example, one can consider two firms desiring to collaborate on a database development project which requires competence in SQL, ER modelling and normalization; a vector with three elements. Figure 1 shows a firm that possesses competency in SQL and normalization but no meaningful capability in ER modelling. Since this competency is required for the project this knowledge element will have to be contributed by the other partner or developed at a cost in resources (e.g. time, money, etc.).

The parsimony of a binary element vector representation allows us to draw on the vast domain of multivariate analysis and adapt proximity measures to define an axis, which we use to define KC with a higher level of precision than is currently the case.



Vector elements
1- Mostly present. Sufficient to be considered extant, usable and extensible.
Possessor has sufficient absorptive capacity to assimilate similar analogous facts.

0 – Mostly absent. Ill defined or loosely possessed. Not sufficiently present to create meaningful useable ability.

Figure 1: Knowledge as a Vector

THEORETICAL DEVELOPMENT/MODEL

With a vector representation of knowledge we may evaluate how separately possessed knowledge stocks can be combined super-additively – the combined knowledge base has a higher semantic level than the simple sum of its individual parts

- the essence of KC. In individual piece of knowledge (e.g. competence in SQL programming) may *enable* other competences or may be *sequential* to other knowledge stocks (i.e. required as part of a sequence of knowledge objects).

In the previous database example, a firm lacked a key knowledge object and needs to either develop it on its own, at a cost, or collaborate with a partner firm possessing the requisite knowledge. Then, either firm should be capable of absorbing the shared knowledge at a minimum cost.

The ability of a firm to absorb knowledge is dependent on its absorptive capacity (cf. Cohen & Leventhal, 1990). In the interest of brevity, we take absorptive capacity to mean the ability to absorb new knowledge that is diverse yet partially related to the existing knowledge base. This applies to the concept of KC by extending the vector model to use measures of proximity used in cluster analysis (distance between vector objects).

In the original model of Cowan & Jonard (2009), the expected value of an alliance varies along a symmetrical curve using *overlap* in knowledge between the two partners as the independent variable. With no overlap, the benefit of collaboration is less than the cost because the two partners have little common knowledge and lack a shared ‘vocabulary’ – a lack of absorptive capacity. The recipient lacks enough associated knowledge to assimilate the new knowledge provided. The other extreme is complete overlap of knowledge elements. Here there is very little joint benefit in exchange because the available knowledge is common between the two; there is nothing new to exchange (or absorb).

To capture the essence of acquiring novel knowledge by associating it with existing knowledge, as described in this conceptual framework, we add a second dimension – diversity. *Diversity* of knowledge is a measure of how different the knowledge base is between the two actors. Thus, absorptive capacity represents both the overlap of the knowledge bases *and* its diversity – both can be measured using existing proximity measures.

Using diversity and overlap as axes, a response surface for KC is defined (see figure 2). From this surface characteristic curves can be extracted to model types of KC and associated behaviors. Characteristic curves have been used in cognitive psychology (e.g. Norman, 1975; Navon & Gopher, 1979) to model mental capacity requirements arising from two sensory channels (e.g. auditory and visual stimuli).

Let the following coefficients be defined with respect to two knowledge vectors, V_1 and V_2, as counts of vector element pairs:

S11 – both vector elements present
S01 – absent/present
S10 – present/absent
S00 – absent/absent
N – vector dimension; how many elements comprise the knowledge base.

For example if V_1 = {0,0,1,1,0} and V_2={1,1,1,0,0} N=5 the indices are: S11=1, S01=2, S10=1 and S00=1.

To define the axis for knowledge **overlap** we use the Russel-Rao proximity measure (Rao,1973), S11/N. The axis representing knowledge **diversity** is adapted from the Jaccard proximity measure (Jaccard & Wan, 1996;Lattin, Carrol & Green,2003) to exclude the S11 coefficient and is defined as (S01 + S10)/N. Figure 2 shows the axis for overlap and diversity and how KC is modeled as a response surface (shown notionally in grey) whose value, **L**, represent the level of complementarity.

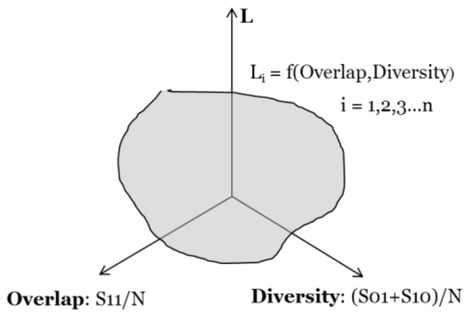


Figure 2: KC as a response surface (surface is notional)

The response surface shown in figure 2 is defined over the two axes described while the vertical axis, **L**, represents the level of KC ranging from 0.0 (no-KC) to 1.0 (total KC).

Types of KC and Behavioral Implications

The original 2D model (Cowan & Jonard, 2009) is the level of KC (L-axis) and overlap axis shown in figure 2. To extend this to a 3D model the curve on the Overlap-L plane can either be rotated about the vertical axis (figure 3; left panel), L, or extruded (figure 3; right panel). This gives rise to two types of knowledge complementarity response surfaces (level of KC, labeled Kc in the figure) shown in figure 3.

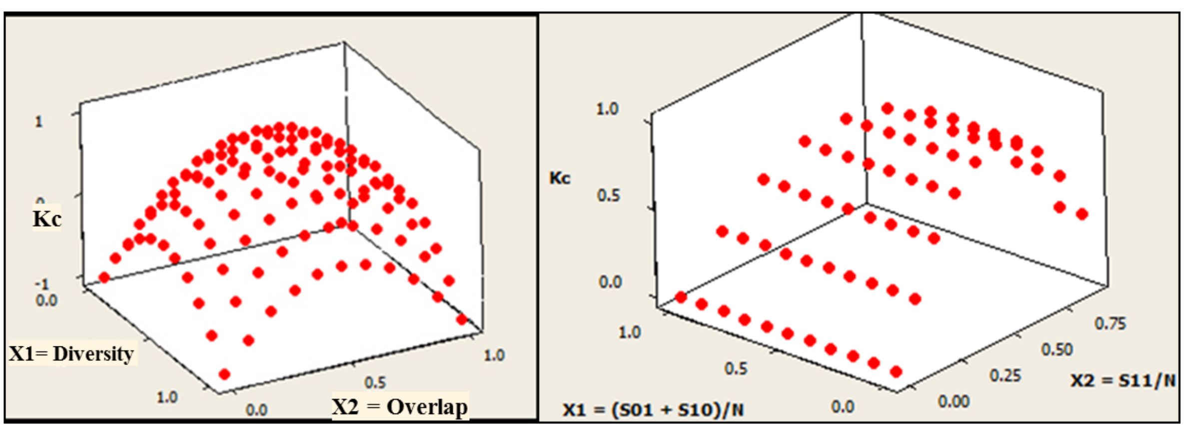


Figure 3: The Level of Knowledge Complementarity as a Response Surface

In between these two closed-form, analytical shapes are an infinite number of shapes that comprise the most general case. These parabolic shapes are because it is consistent with the original 2D model (Cowan & Jonard, 2009, Normal & Bobrow, 1975, Navon & Gopher, 1979) and curves extracted from them have behavioral interpretations in the context of absorptive capacity.

From each surface can be extracted a curve at a given level of KC, 0.0≤**L**≤1.0. The shapes of these curves influence how the two partners will interact with each other. Let's start with the degenerate case of **no-KC** (figure 4a) where neither actor requires knowledge from the other. This condition can arise when there is no overlap between the two and thus no common 'language'. The other extreme of no-KC is where the knowledge base is common between the two and thus common knowledge. There can also be intermediate combinations of overlap and diversity that result in no-KC because of insufficient overlap and/or diversity at that level of KC.

Channel-like KC (Figure 4b) portrays a body of knowledge that is not indigenous to either firm but components of which is supplied to the relationship at a fixed proportion for exchange to occur at a given
level. This contribution is knowledge; however, it is insufficient for the independent execution of the task. The productive capability exists only within the focal channel. If either party fails to contribute the required knowledge component, then knowledge sharing is degraded or precluded, while excessive contribution has no effect. For example, suppose the parties agree to L1 – a desired channel performance – which requires contribution x1 from actor x and y1 from actor y. Should actor y benevolently increase its contribution unilaterally to y2, the channel performance does not increase. The surplus contribution alone cannot increase channel performance because it may be irrelevant to performance at that level or even incomprehensible to actor x (who may not be able to make use of the offered knowledge) – i.e., x may not possess the necessary absorptive capacity. However if both members of the dyad are willing and able to increase their respective contribution from (x1,y1) to (x2,y2) then a higher level of exchange, L2, is possible.

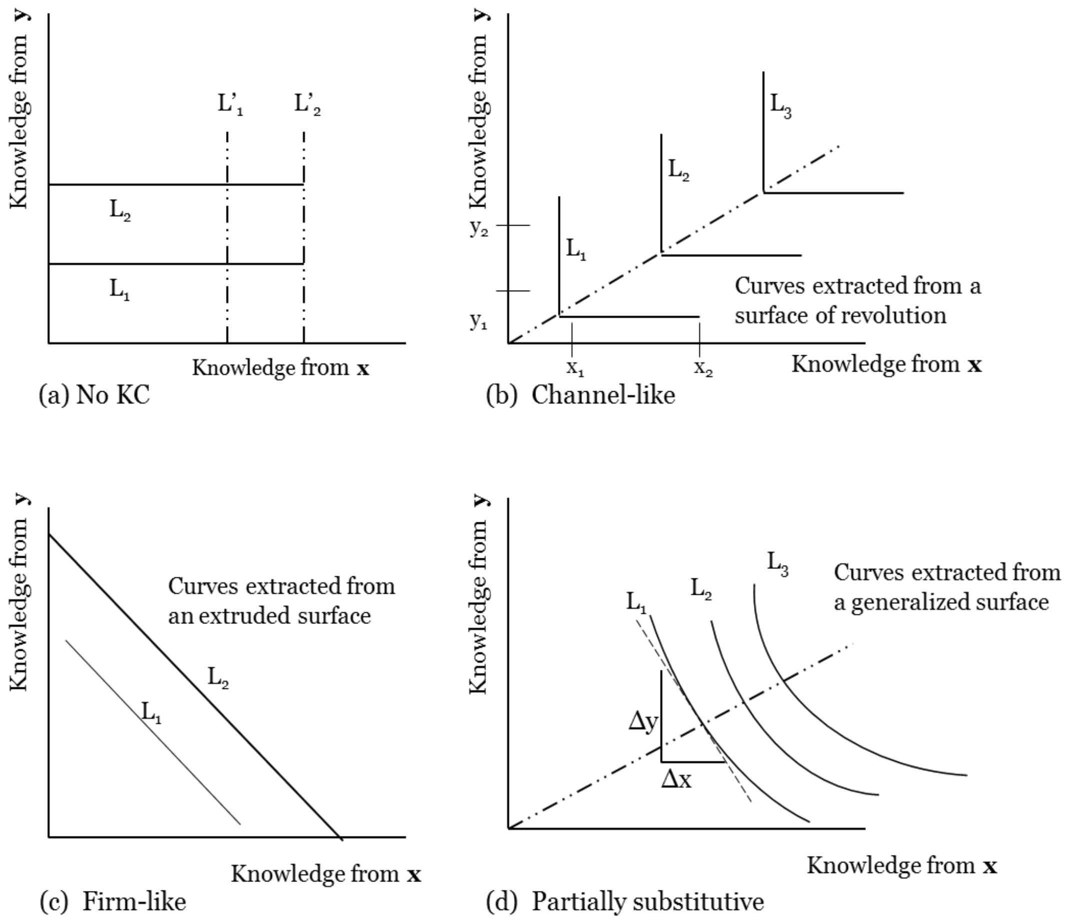


Figure 4: Types of Knowledge Complementarity
*Source: adapted from (Navon & Gopher, 1979; Norman & Bobrow, 1975)

Firm-like KC (Figure 4c) represents the condition where the knowledge of either party may be independently sufficient for the execution of the task. However, for reasons not specific to the nature of the knowledge, the actor chooses to use knowledge from the partner instead of an internal source. There are two distinguishable types of firm-like KC: mostly firm-like (L1) and totally firm-like (L2). Mostly firm-like KC occurs when each of the actors has almost the entire knowledge base necessary for the product but missing a key capability. This is why in Figure 2c L1 does not have intercepts because the knowledge possessed by that firm is not complete. This missing competency could be indigenously developed at a cost as an alternative to a knowledge sharing relationship. Totally firm-like KC results when both actors do possess the requisite knowledge but chose to still exchange knowledge in a dyadic relationship. This may, perhaps, reflect internal operational concerns such as resource allocation preferences, capacity constraints or economies of scale, etc.

Partially substitutive KC (Figure 4d) is a generalization of firm-like and channel-like KC. In channel-like KC neither firm is independently capable of process execution whereas in firm-like KC either firm is independently capable. Thus, partially substitutive KC is an intermediate position on a continuum bounded by channel-like and firm-like KC. Either, or both, members of the dyad have knowledge capabilities insufficient, or inefficient, for independent performance as in firm-like. However, unlike pure channel-like KC, the respective marginal knowledge contributions from each partner could be altered. Thus, a firm may enter into a partially substitutive supply channel relationship because the contribution required also enables it to develop a firm-like capability and the existing capability is such that it is not wholly dependent on the partner as in channel-like.

This conceptualization has presented a more precise way to characterize knowledge complementarity and knowledge exchange behavior. ICT has tremendously increased the ability to create and combine knowledge stocks and has dramatically altered the nature of collaboration behavior across boundaries involving distinct bodies of knowledge.

The digital nature of computers strongly suggests the need for less subjective definitions of knowledge complementarity and the behavioral changes resulting from a data-immersive environment. This is consistent with current themes like ‘big data’ or ‘business analytics’ except for being focused on organizational behavior resulting from cheap ubiquitous ICT.

Implications for Future Research

While a theoretically grounded basis for KC types and their underlying generating surfaces, as introduced in this paper, are necessary, it is not sufficient. Empirical validation is needed for each type of KC. Math modeling could be an interesting supporting development but a data-driven methodology appears to be best suited to account for the behavior components that inevitably underpin collaboration.

Since there does not appear to be an existing survey instrument related to the four KC-types presented and derived using absorptive capacity we offer some concluding perspectives to aid in future research. These suggestions are not intended to be exhaustive, or even theoretically rigorous, but rather serve as a basis for further development. To move further, it is important to consider the right supplier buyer-relationships.

Figure 5 presents a KC typology based on two parameters: Integrative Patterns and Innovation Orientation. In this work, *Integrative Patterns* defines the relationship between the knowledge sharing partners. If both agents (i.e. “buyer” and “supplier”) are members of the same organizational unit (e.g. business unit) then their relationship would be characterized as *interpersonal*. This would have aspects of both social and professional interactions. In contrast, a *virtual* integrative pattern occurs when the agents operate across organizational boundaries. While possibly still having social aspects, these are secondary to the effects of having separate lines of accountability (i.e. the agents act for different organizational entities).

The second parameter - *Innovation Orientation* – relates to motivation to share knowledge and the effects of knowledge complementarity (KC). If KC results in an emergent capability then the Innovation Orientation is *Discovery-based*. If the effect of

KC is to enhance or extend an extant capability (e.g. process improvement) then this type of KC would be considered *delivery-orientated*.

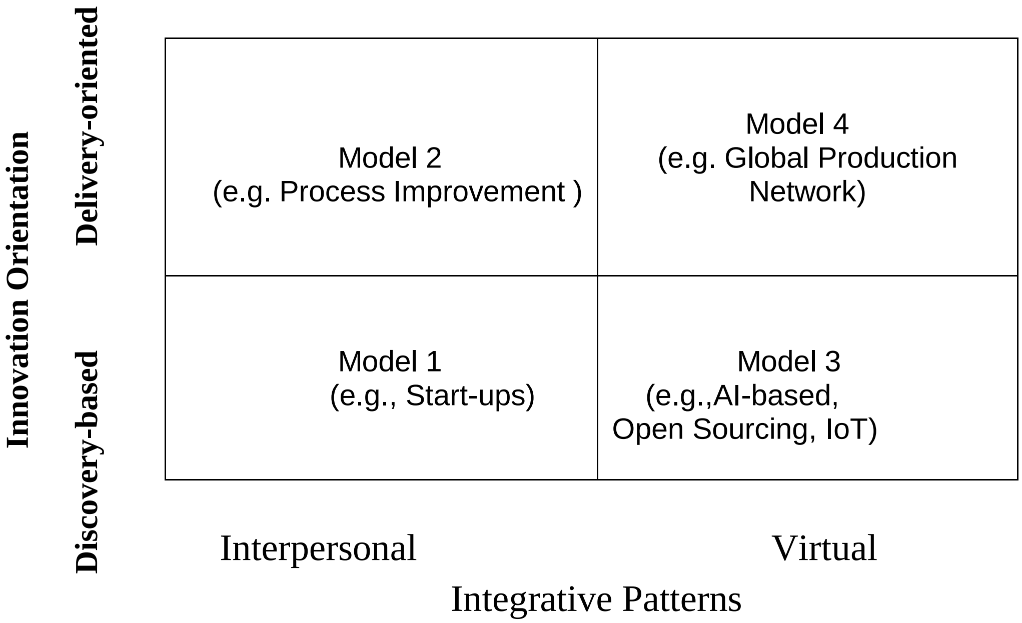


Figure 5: A KC Typology

Given a non-zero level of KC, the motivation for knowledge sharing can be characterized by the KC typology shown in Figure 5.

Model 1: Start-ups KC. The start-up may have different founders who are geographically-connected and highly interactive in their interpersonal relationships. The main focus is to discover innovative ideas that have high potential for commercialization success. Here, supplier-buyer relationships are agents acting as suppliers and buyers [of knowledge] providing and using knowledge to develop and commercialize ideas and initial product offerings.

Model 2: Process-based KC. The actors contribute a desirable proportion of knowledge for a given level of process innovation. Depending on the complexity of the requirements for process innovation, actors adjust their level of knowledge contribution and move longitudinally along the surface (figure 3, right panel) and not to a higher level of KC. Here, suppliers are internal problem solving consultants that define the nature and scope of innovation. The buyers are senior management of manufactures or sales organizations that intend to raise productivity of production processes or distribution channel.

Model 3: Third, AI-based, IoT and Open Sourcing KD. The interactions are quite virtual in using open sourcing innovation ideas, integrating the AI-based simulation findings, and developing internet-based discovery knowledge to engage in diverse centers of innovation activities. Here, suppliers are external innovative idea generators that provide the innovative technology frontiers for value creation. The buyers are innovative investors and R & D organizations that seek to secure new growth engines for future business lines.

Model 4: Fourth, global production network KC. Manufacturing firms that have a variety of production units around the world requires virtual knowledge sharing mechanisms with productivity-driven implementation goals. Here, suppliers are process innovation expert teams at corporate headquarters and regional centers (along with associated with expert advisory teams) that provide the diagnosis and prescriptions for troubles, issues and conflicts arise. Buyers are affiliated production network participants for delivering economies of scale and scope goods and services.

Our follow-up studies present (1) testable hypotheses with our initial framework; (2) case study results on four different types of KC.

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