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A Theoretical Model of Information Systems Analogical Learning

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Abstract

As organizations routinely replace information systems to support evolving business needs, employees must often adapt to new systems to complete familiar tasks. Despite widespread acknowledgment of the learning burden imposed by such transitions, the cognitive processes that guide users' adaptation, particularly how prior system knowledge is leveraged, remain under-theorized in the information systems literature. This paper introduces ***Systems Analogy Learning Theory (SALT)****, a cognitive framework grounded in analogical learning theory, to explain how users draw on mental models of a prior (base) system to make sense of a new (target) system. SALT outlines a process of analogical reasoning composed of access, mapping, and transfer, and identifies four prototypical learning pathways based on users' perceived surface and structural similarities between systems. These pathways are theorized to yield distinct learning trajectories and implications for training and system design.*

Keywords: systems switching, analogical learning, software training

1. Introduction

In today's dynamic digital workplace, employees are frequently required to switch from one information system to another as organizations adopt new technologies to support existing work processes. These changes often involve replacing a familiar software system with a new one intended to serve the same functional purpose. Systems switching is accelerating, driven by technological innovation, organizational change, and digital tool proliferation. Whether prompted by system upgrades, vendor transitions, mergers, or shifts in organizational strategy, the migration from one software system to another has become a routine part of professional life.

Each transition between systems introduces a new learning burden for employees. Users must learn new interfaces while reconstructing how their tasks map to system capabilities. This learning process is often complicated by limited training, time pressure, and the assumption that experience with a prior system will naturally transfer to the new one. Yet successful adaptation depends on more than surface similarities; it requires employees to form accurate mental models of the new system while drawing on prior knowledge in meaningful ways. Understanding how individuals reuse prior knowledge is critical for adoption, productivity, and training design.

Despite the pervasiveness of software switching in contemporary organizations, research has yet to fully explain how users cognitively adapt to new systems by drawing on prior experience. While information systems (IS) studies have examined factors such as user satisfaction (e.g., Au et al., 2008; Gable et al., 2008; Vaezi et al., 2019), training effectiveness (e.g., D. L. Davis & Davis, 1990; Gupta et al., 2010; Sharma & Yetton, 2007), and technology acceptance (e.g,. F. D. Davis, 1989; Delone & McLean, 2003; Venkatesh et al., 2003) during system implementation, less attention has been paid to the *knowledge transfer process itself*, particularly how users make sense of a new system based on their understanding of a previous one. Existing models of system adoption often assume a *tabula rasa* approach to learning (Dang et al., 2017), neglecting that users do not approach new systems as novices, but rather bring mental models shaped by prior interactions. Moreover, although end-user training research has acknowledged that prior system knowledge can inform reasoning about new systems via an analogical mapping process (Bostrom et al., 1990; Shayo & Olfman, 2000), it is largely silent on how and when this knowledge transfer occurs. This oversight leaves a theoretical gap in explaining why some users adapt smoothly while others struggle, even when system functionalities are ostensibly similar. Addressing this gap requires a cognitive account of learning that describes how analogical reasoning—comparing the known with the unknown—plays a central role in navigating system transitions.

This paper proposes a new theoretical framework, *Systems Analogical Learning Theory (SALT)*, that explains how a user's knowledge of a previous system is transferred to a new system through an analogical reasoning process. Drawing on literature in analogical learning, IS training, and human-computer interaction, we posit that users form *mental models* of information systems and their associated tasks, which consist of both surface and structural components. We suggest that when a user switches to a new system to perform the

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same task, she naturally draws from her mental model of the previous system to inform her understanding of the new system via an analogical reasoning process. We draw on analogical learning theory (e.g., Gentner, 1983; Holyoak & Thagard, 1997) to develop research propositions about how, why, and to what extent this analogical learning occurs in a system switching context. The model highlights four archetypal analogical learning pathways that carry implications for user learning and training.

This work makes at least two primary contributions to the IS literature. First, from a *system design* perspective, our model provides a framework that can inform the design of systems intended to replace other systems in the support of work tasks. Designing systems around users' mental models of tasks has long occupied the attention of HCI researchers (Hu & Twidale, 2023; Payne, 2012); yet despite early attention to this area (e.g., McDonald et al., 1986), the literature still lacks a comprehensive model that offers specific predictions about how knowledge of a particular prior system can translate to a new system. Second, from an *end-user training* perspective, our model can help organizations to predict where learning difficulties are likely to occur based on the comparative alignment between mental models of old and new systems. Understanding the principles that govern analogical IS learning can not only help firms anticipate employees' learning obstacles, but can also guide the creation of tailored training programs that efficiently leverage the analogical learning that is taking place.

2. Background

Because this is a theory development paper, we conducted a targeted review of IS literature on analogical learning, training, and system switching, drawing on both foundational cognitive psychology and IS/HCI studies. Articles were selected based on their theoretical relevance rather than exhaustiveness, consistent with theory-building approaches.

2.1. Systems Switching

Switching from one information system to another to support a work task is a common facet of organizational work that has been studied by previous IS researchers (e.g., Bhattacherjee et al., 2012; Ye & Potter, 2011). Whether the switch occurs by the user's choice or organizational mandate, switching systems introduces challenges that users must overcome to use the system effectively. Often termed "switching costs", these challenges include uncertainty costs (psychological discomfort or anxiety about the new system), transition costs (time and effort expended during the change), loss costs (loss of benefits like power, position, and control) and reduced performance costs (loss of efficiency during transition), among others (Dang et al., 2017; Polites & Karahanna, 2012). One type of switching cost identified by prior research as a key barrier to effective system switching is the burden of *learning* to use a new system (Chen & Hitt, 2006). Although some studies have found that learning costs were not a significant predictor of the *intention* to switch systems (Dang et al., 2017), their effects on subsequent implementation and training outcomes have been well documented in the IS literature (e.g., Gupta et al., 2010; Robey et al., 2002; Sharma & Yetton, 2007). Nevertheless, although learning a new system is recognized as critical, little research examines how prior system knowledge affects learning costs

2.2. Analogical Learning

When facing the unfamiliar, people often learn by relating it to the familiar—that is, by analogy. Analogical reasoning occurs across domains from problem solving to scientific discovery (Gentner et al., 2001). IS scholars have long recognized analogy as a central mechanism by which individuals learn to use information systems. Early HCI research observed that "left to themselves, novice computer users will spontaneously generate analogies and use them to reason about the system" (Halasz & Moran, 1982, p. 383). For example, Douglas and Moran (1983) found that individuals drew heavily from their operational knowledge of typewriters when learning to use command-based text editing software. Analogical learning was also found when moving from one text editor to another (Polson et al., 1986), prompting efforts to quantify learning times or conceptual usage errors based on the amount of anticipated knowledge transfer between two systems (Young & Whittington, 1990).

The importance of analogical learning has also been recognized in IS training research. In their foundational work on end-user training, Bostrom et al. (1990, p. 103) proposed that effective use of a system required the development of an accurate mental model, or a user's "internal representation of the system structure and function that provides explanatory and understanding power." According to the authors, such a mental model can be formed in three ways: via training, via usage of the system itself, and via analogy, wherein "users can acquire a mental model of a new system by drawing analogies from similar systems that are available to them" (Bostrom et al., 1990, p. 103). However, beyond identifying analogy as an essential learning mechanism, this work has not offered theoretical insight into how analogical IS learning occurs and when it may be beneficial or harmful (Halasz & Moran, 1982).

2.3. The Analogical Learning Process

Analogical learning is the process by which knowledge from a well-understood *base domain* is applied to a less-understood *target domain*. This knowledge consists of mental representations of domain *objects* characterized by *attributes* and connected via *relations* (Gentner, 1983). Two prominent theories—Structure Mapping Theory (SMT; Gentner, 1983; Gentner & Markman, 1997) and Multiconstraint Theory (MCT; Holyoak & Thagard, 1989, 1996, 1997)—offer complementary accounts of this process, typically comprising three key stages: access, mapping, and transfer.

The first stage, *access*, concerns the activation of one or more base domains in the learner's memory when confronted with the novel target domain. This process relies on the learner perceiving enough similarity to recall a prior domain as relevant. For instance, a student learning about electricity might recall water flow as a familiar system that behaves similarly (Gentner, 1983). Once a base domain is accessed, the learner engages in *mapping*, aligning relational correspondences between base and target elements. In our example, water pressure may be aligned with voltage, pipe diameter with wire gauge, and valves with switches, creating a structure for the learner to reason about the unfamiliar system. In transfer, learners apply inferences (e.g., voltage drives current as pressure drives water). Valid inferences aid learning; mismatches hinder it.

The result of transfer can vary based on the types of mappings drawn. Theory suggests that analogical learning may be attempted based on perceived similarity between domain attributes, relations, or a combination of the two (Holyoak & Thagard, 1997). Analogies based solely on perceived attribute similarity are called *mere appearance comparisons* (Gentner, 1983; Gregan-Paxton & John, 1997) and may impede learning outcomes. For example, attempting to learn about electrical circuits by drawing analogical comparisons to glow sticks based on the fact that both produce light is likely to produce little valuable insight due to the fundamental differences in the processes that underlie these systems. On the other hand, analogies may be drawn as *relational comparisons* between two domains that share few surface features, but are characterized by parallel relations between objects (Gentner, 1983; Gregan-Paxton & John, 1997). The electrical circuit and water flow domains are good examples of contexts with few surface attributes but similar relational qualities. In these cases, relational alignment allows the learner to abstract common structure, resulting in a more flexible and abstract knowledge structure, or schema. Finally, domains that share attribute and relational similarities may be mapped using *literal similarity* comparisons (Gentner, 1983; Gregan-Paxton & John, 1997) where users may effectively replicate their base knowledge.

2.4. Systems Mental Models

To guide our theorization of analogical learning in a system switching context, we first examine the cognitive representations of systems that guide this learning process. An abundance of human-computer action research has postulated that users' interactions with systems are guided by *mental models* of these systems (e.g., Bostrom et al., 1990; Payne, 2012; Shayo & Olfman, 2000). "A mental model of a dynamic system is a relatively enduring and accessible, but limited, internal conceptual representation of an external system whose structure maintains the perceived structure of that system" (Doyle & Ford, 1998, p. 17). Mental models help people interact with systems, predict outcomes, and guide behavior (Bostrom et al., 1990).

In parallel with the notion of attributes and relations in analogical learning theory, Shayo and Olfman (2000) note that a system's mental model consists of declarative and procedural knowledge substructures relating to the use of the system to perform a task. Concerning the declarative substructure, mental models of systems contain representations of *system components*, including the system's key elements or objects with which the user can interact. For example, an email client system includes objects such as an inbox, folders, contacts, and a compose mail feature. In examining users' mental model formation of a medical information search system, Zhang (2010) found that users' mental models represented core system components such as a search bar, databases, hyperlinks, etc. The declarative substructure also consists of knowledge about the specific *user interface* of the system, which includes representations of the system's layout and visual structure. For example, the "Compose Email" button is in the top-left corner, and the gear icon signals settings. In Zhang's (2010) study, elements of the user interface, "including menus, side bars, tabs, hyperlinks, sub-headings, and bold font" (p. 2210) also featured prominently in users' mental models of the information retrieval system they used.

The procedural substructure includes the goal-oriented aspects of accomplishing a task using the system. This part of the mental model contains representations of *system behavior/relationships* that predict how components behave and are interrelated in cause-effect patterns. For example, clicking "Send" in an email client tool will send a composed email, while clicking "Delete" will move the email to the deleted mail folder. Representations of system behaviors allow users to simulate outcomes based on mentally enacting how its components interact (Johnson-Laird, 1980). The effect of induced or derived mental models on a user's ability to understand and predict system functions was a core focus of early HCI research (e.g., Gentner & Schumacher, 1986; Kieras & Bovair, 1984). Finally, knowledge of system behavior and relationships can be aggregated to larger *task representations* that embody the higher-level steps that users follow to complete a task using the system. For example, to send a document to a group of recipients, one must create a contact group, compose an email, attach a local file, and send the email. In her empirical study that elicited mental model components, Zhang (2010) found that in addition to the declarative and interface knowledge described above, a mental model of a system "also encompasses procedural knowledge of solving problems using the system" (p. 2210), including the sequence of steps users would follow to achieve their goal.

The components of systems mental models described above can be usefully correlated with the core concepts of analogical learning theory (Gentner & Schumacher, 1986). The declarative aspects of the mental model, comprising knowledge about the system's objects and attributes and the user interface, constitute *surface-level* knowledge about the system. This level of knowledge allows users to recognize user components and understand broad system features, but does not permit deeper reasoning about system behavior or using the system to achieve a goal. On the other hand, the goal/procedural aspects of the mental model constitute the *structural-level* knowledge about the system; namely, how the components of the system interact to support completion of a task.

3. Systems Analogical Learning Theory (SALT)

Based on the theoretical background described, we propose the Systems Analogical Learning Theory (SALT) as a theoretical framework for understanding how analogical learning occurs in system switching. At present, we limit the scope of our theory to the context of a user migrating from one *operational* information system (i.e., a system designed to support the completion of discrete business procedures or tasks) to another to support the same work task.

The core theoretical tenets of SALT follow the general stages of the analogical reasoning process outlined earlier, and are presented graphically in Figure 1 below. The model depicts four prototypical analogical learning "pathways" depending on how users map both surface and structural features of their base system mental model to a target system. Naturally, learning to use any information system is a process that will involve many learning iterations and rely on various levels of analogical reasoning; thus, our model is necessarily a simplification of this process. Nevertheless, identifying these archetypes of systems analogical reasoning can offer a valuable framework for understanding how prior system knowledge influences learning trajectories when migrating between systems.

In the following sections, we develop seven core research propositions of the SALT model (identified in Figure 1 as P1, P2, etc.) that can guide future empirical work in this area.

3.1. Access

P1: When switching to a new system, users naturally access their mental model of their previous (base) system to attempt to understand the new (target) system.

Our first proposition deals with the access stage of the analogical learning process. Several points of evidence from extant literature support the notion that the mental model of a base system serves as a natural starting point when learning the new system. First, when switching to a new system to perform the same task, users bring their pre-existing knowledge and expectations, often shaped by using a prior system. In their study examining how users learn new but similar software packages, Shayo & Olfman (2000) note that drawing analogical linkages with prior software systems is a primary mechanism for mental model formation of the target system. Their experimental study showed that participants who had been previously exposed to different but related software packages had enhanced training outcomes (e.g., mental model accuracy, self-efficacy) related to a target software package than those who lacked this exposure, indicating that they spontaneously transferred their knowledge from one system to the next. Other empirical fieldwork (Fadel et al., 2008, p. 24) reports statements from enterprise system trainees that reveal their reliance on prior system knowledge:

- "If [trainers] had known [our old system], they would have been much more effective. We needed to hear from them, 'This is what [the old system] does – here's how [the new system] does it.' Instead, they came in wanting to put [the old system] out of your mind."
- "We need a [old system] vs. [new system] document. 'If you do X this way in [the old system], you do it this way [the new system].'"

Finally, the notion that a mental model of a base system would automatically be recruited in learning a target system is also supported by the MCT model of analogical learning, which predicts that goal similarity (e.g., trying to perform the same task) triggers retrieval of structurally or semantically similar base domains

(Holyoak & Thagard, 1997). That is, the "pragmatic constraint" of needing to perform the same work task will naturally invoke the retrieval of knowledge structures most closely related to the task (Thagard et al., 1990). For instance, an HR specialist moving from PeopleSoft to Workday is likely to immediately recall familiar tasks such as generating a payroll report, even before understanding the new interface.

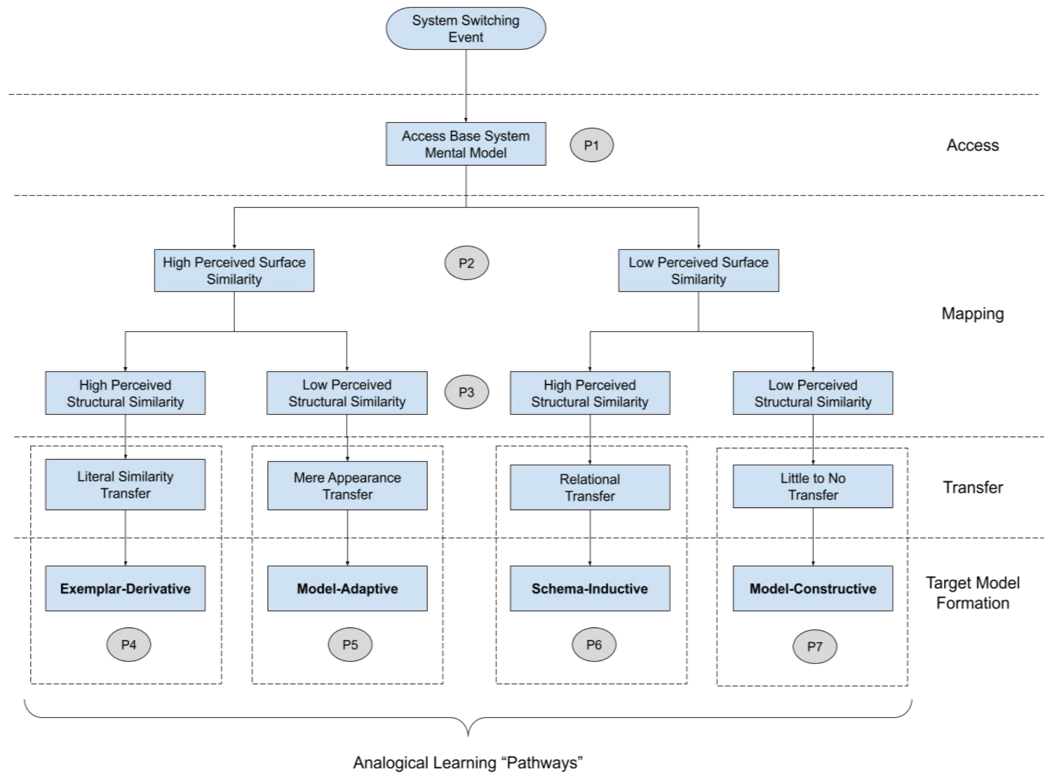

Figure 1. SALT Theoretical Model

3.2. Mapping

P2: Users first evaluate potential similarities between the surface features of the base system mental model and the perceived surface features of the target system.

P3: After evaluating surface similarities, users evaluate potential similarities between the structural features of the base system mental model and the perceived structural features of the target system.

After the base mental model has been accessed, the next step in the analogical learning process is mapping, wherein the user attempts to draw correspondences between elements of the base system mental model and the target system. We theorize that mapping occurs first at the *surface level*, as users look for similarities in the system objects and layout across the two systems (Blanchette & Dunbar, 2000). Users' first exposure to a system is its interface, where affordances shape initial expectations (Norman, 2002). For example, when first encountering Salesforce after years with Microsoft Dynamics, a sales manager may recognize familiar tab names ('Leads,' 'Opportunities') and infer that the systems are similar to each other. This notion is also supported by the MCT (Holyoak & Thagard, 1989, 1997), which argues that surface (semantic) similarity is often the first clue to initiate analogical mappings between a base and a target.

Once users have oriented themselves to a new system by identifying surface-level cues, such as familiar labels, icons, or interface layouts, they move to a deeper stage of analogical reasoning to evaluate structural similarities between systems. In this phase, the user attempts to align the underlying functional or causal relationships from their prior (base) system with those perceived in the new (target) system. For the sales manager who recognized similar tabs between Microsoft Dynamics and Salesforce, she may subsequently infer that clicking these tabs will produce a similar sequence of steps for managing these sales activities. This shift from surface to structural comparison aligns with SMT (Gentner, 1983), which posits that analogical learning depends not merely on shared attributes, but on the alignment of relational structure—the way components interact or depend on one another. According to the systematicity principle of SMT, users prefer analogies that map higher-order, interconnected relationships, such as task sequences or data flows, over isolated or superficial similarities (Clement & Gentner, 1991; Gentner & Kurtz, 2006).

Empirical studies in analogical transfer further support this view. Holyoak and Koh (1987) demonstrated that successful knowledge transfer across domains occurs primarily when individuals detect deep structural parallels, even when surface features are dissimilar. Similarly, Gentner et al. (1993) distinguished between retrievability (which is often surface-driven) and inferential soundness (which depends on relational alignment). Their findings suggest that while surface similarity facilitates initial access to a prior mental model, the recognition of structural similarity enables meaningful adaptation and learning.

3.3. Transfer/Model Formation

P4: Successful mapping of perceived similarities in both surface and structural features will yield:

a. A "literal similarity" transfer where both surface and structural elements of the base mental model are successfully applied to the target system

b. An exemplar-derivative model formation process where the mental model of the target system is closely tied to the mental model of the base system

When users successfully map both surface and structural features from a base system onto a new target system, the result is a form of analogical transfer often referred to as "literal similarity" (Gentner, 1983). In such cases, the new system closely resembles the old one in appearance (e.g., interface elements, labels, or navigation) and underlying functional or causal structure (e.g., workflow logic, data dependencies, or input-output relationships). With both similarities present, users can apply prior mental models with little adaptation. For example, when upgrading from one version of Epic electronic health records (EHR) to the next, users can apply their existing mental models almost directly.This yields a particularly efficient form of transfer, where learning is fast, cognitive load is low, and the user's performance in the new system reflects deep familiarity (Gentner & Schumacher, 1986). Research has shown that analogical mapping is more intuitive when literal similarity is present (Gentner & Kurtz, 2006; Gentner & Markman, 1997).

This kind of transfer also leads to what is known as exemplar-based learning, in which the mental model of the target system remains closely tied to that of the base system. Rather than forming a fully abstracted schema, the user's understanding of the new system is anchored to a specific past experience, namely, the previous system. In practice, the target system is interpreted not as a distinct conceptual domain, but as an extension or direct analog of the base. This aids short-term adaptation but may constrain flexibility if the new system evolves. Exemplar-based learning may be a satisfactory outcome in contexts where systems are intentionally designed to mimic predecessors to reduce training time and increase adoption rates.

P5: Successful mapping of perceived similarities in only surface features but not structural features will yield:

a. A "mere appearance" transfer where only surface elements of the base model are successfully applied to the target system

b. An adaptive model formation process where the mental model of the base system must be adjusted from (and may interfere with) the formation of the mental model of the target system due to apparent similarity but structural misalignment

When users identify similarities between the surface features of a base system and a new target system, but fail to detect or correctly map underlying structural relationships, the result is what SMT terms a "mere appearance" comparison. In these cases, transfer is driven by superficial resemblance, such as familiar icons, menu labels, or interface layouts, without corresponding similarity in how the systems function or tasks are accomplished. These cues may orient users but also mislead them into assuming false equivalence. Users may make inaccurate assumptions about how the new system works because only surface-level elements of the base system's mental model can be mapped. This can result in confusion, misuse of system features, or even task failure, especially in domains where correct relational understanding is essential for successful operation (Gentner & Schumacher, 1986; Kieras & Bovair, 1984). For instance, a payroll clerk may see a familiar 'Submit' button in Workday but find it triggers a multi-step approval workflow rather than the single-step process in PeopleSoft, leading to errors from over-relying on surface similarity.

Because the more important structural features of the target are distinct from the base, mere appearance comparisons require adaptation of the base mental model to accommodate these differences. If such adaptations are not made, the cognitive consequence can be a negative learning outcome in which the user's prior mental model interferes with the development of a correct understanding of the target system. This negative transfer occurs when surface similarity leads users to overgeneralize from a familiar system, resulting in persistent errors or resistance to learning new structures. Empirical studies show that when users rely heavily on surface features and fail to grasp structural mismatches, they are not only less effective at task execution but may also develop false confidence in their understanding, leading to slower correction and greater frustration (Gentner & Schumacher, 1986).

P6: Successful mapping of perceived similarities in only structural features but not surface features will yield:
a. A "relational" transfer where only structural elements of the base mental model are successfully applied to the target system.
b. A schema-inductive model formation process where the relational aspects of the mental models of both systems are abstracted into a more generic mental schema representing the functionality of both systems

A target and base system may sometimes share common procedures and dependencies for completing a task, but diverge in their surface features (i.e., different names for key system objects, different screen layouts, etc.). Even if users fail to find congruence between surface elements of the base and target systems, they may still be able to recognize the structural parallels in workflow logic, cause-effect relationships, or data flows. This type of scenario sets the stage for a "relational" comparison. In such cases, knowledge about the procedural aspects of the system can be transferred regardless of surface dissimilarity. Even when surface features diverge, as when moving from a desktop-based accounting system to a cloud-based one, users may recognize that tasks still require the same sequence of structural steps (e.g., inputting journal entries, reconciling accounts, and generating financial statements). As noted earlier, the systematicity principle of SMT posits that higher-order relational mappings are the bedrock of actual analogical reasoning, as they allow the learner to transcend superficial disparity between the target and the base in favor of deeper relational knowledge structures that enable operational inference and goal attainment. Several analogical learning studies have shown that structural similarity can support effective problem solving even when surface characteristics differ.

Although the transfer process in a relational comparison may be less straightforward than a literal similarity comparison due to surface feature variation, it has the potential to yield a more enduring mental model structure. While literal similarity comparisons allow quick mapping across surface and structural features, exposure to structurally aligned but visually dissimilar systems encourages learners to focus on underlying patterns rather than context-specific details. This process results in a more generic and broadly applicable mental model, or schema, that equips the user with a more flexible cognitive framework—one that can facilitate adaptation to future systems that share relational patterns, even if they look entirely different. In this way, relational comparisons may demand more cognitive effort upfront but ultimately yield deeper, more generalizable understanding that supports long-term learning and cross-system transfer.

P7: Unsuccessful mapping of either surface or structural features will yield:
a. Little to no application of the base mental model to learning the target system.
b. A constructive model formation process requiring de novo creation of an entirely new mental model of the target system.

Finally, when neither surface nor structural features of the target and base systems can be mapped, we predict that analogical learning will have little impact on the learning process or outcomes. For example, when adopting a system for an entirely new task domain (e.g., a hospital nurse using an incident-reporting tool with no analogue in the prior system), prior models provide little guidance and the user must build a new mental model from scratch. Of course, other existing knowledge structures (i.e., mental models of systems used to perform different tasks or other software applications in general) may also be recruited during the learning process, but this type of transfer falls outside the scope of our present theoretical consideration.

4. Discussion

4.1. Theoretical Implications

The fact that users bring their knowledge of prior systems to bear on their learning of new systems has been well established over decades of literature in end-user training and HCI (Bostrom et al., 1990; Zhang, 2010). Yet, despite this body of work, we still lack a theoretical framework that explains how this prior knowledge enhances or impedes system learning. Our work extends theories of analogical reasoning into the new domain of system switching. Although some early research in this vein has been done on tools like command-based text editors (Polson et al., 1986) or general device consoles (Gentner & Schumacher, 1986), this work needs to be extended into the realm of modern enterprise software applications. By introducing a taxonomy of analogy-driven model formation processes, the SALT model offers a conceptual framework that helps explain when and why analogical transfer succeeds or fails in IT implementations. Moreover, SALT provides a formal mechanism that connects the structure of mental models with the cognitive dynamics of analogical transfer, helping to clarify how users' internal representations of task logic and system functionality are leveraged across contexts. Given that user learning processes have been an oft-cited but seldom explored facet of technology acceptance literature, SALT can complement other models like TAM or UTAUT by elaborating *how* this learning occurs.

Another theoretical implication of SALT concerns the potential to better understand the effectiveness of end-user software training. Training theorists have long asserted that "analogical mapping" is a central mechanism users employ when constructing mental models of new systems (Bostrom et al., 1990; Shayo & Olfman, 2000). Along with a user's prior beliefs and goals, which have been identified as essential ingredients in the training process (Gupta et al., 2010), the user's prior knowledge plays a significant role. However, by treating the analogical learning process primarily as a black box, this literature has thus far offered limited insight into how different training methods might be selected based on anticipated analogical mapping between systems. Based on the propositions of SALT, it is reasonable to assume that some types of training may be more effective than others depending on the type of analogical mapping required by a particular software migration. For example, training that explicitly maps old and new system interfaces while emphasizing the shared relational structure may be most effective if two systems are aligned mainly structurally but with few shared surface features. For literal similarity matches, perhaps little to no training would be required. By delineating expected learning outcomes of different mapping types, SALT offers new avenues of theoretical inquiry for scholars to explore related to training effectiveness. For example, matching SALT learning pathways with specific theories of adult learning and instructional design (e.g., Merrill, 2002) could offer a novel approach for maximizing efficiency and effectiveness of training programs.

4.2. Practical Implications

For practice, applying the SALT model could have several impactful implications for implementing systems design, selection, and training. From a selection/design perspective, organizations evaluating options for software replacement can use SALT to understand what learning challenges are likely to confront users of new software applications. For systems developed in-house, designers can implement user interfaces and supported workflows that leverage prior system knowledge in purposeful ways. For example, designers may choose to preserve underlying structural features of systems for specific tasks while intentionally modifying surface features to enhance process efficiency or reduce errors. For off-the-shelf software, the SALT propositions can inform comparisons of alternative systems vis-à-vis currently used systems. Evaluating potential systems through a SALT lens can help purchasing teams decide between systems that offer similar functionality but differ markedly in the learning burden placed on employees.

Evaluating training needs and implementing training programs is another area where SALT could offer significant practical benefit. Organizations spend billions annually on IT training, yet effectiveness remains mixed. As noted earlier, trainees often report that IT training fails to help users navigate new system functions in light of their prior knowledge (Fadel et al., 2008). While the literature has offered guidance to organizations about selecting training programs based on learning styles, software type, and task complexity, it has largely been silent on how different levels of mapping between old and new system knowledge might influence the effectiveness of training approaches and modalities. Rather than employing a generic, one-size-fits-all training program, SALT provides a means for helping training designers to provide intentional scaffolding that aids in this mapping. For example, where surface features differ but structural logic remains, training can explicitly emphasize relational mappings to promote schema-based transfer. Training programs can preempt potentially negative transfer outcomes in cases of high surface similarity but deep structural divergence by alerting users to structural differences. For example, training materials can identify potential mismatched mappings and offer side-by-side workflows that help users translate their prior system knowledge to the new system.

The maturation of generative AI represents a timely and complementary co-development of the SALT model. SALT emphasizes the importance of achieving a deep understanding of surface and structural alignment between systems, but the extensive examination and mapping of systems that is required to achieve this goal has traditionally been challenging to operationalize at scale. Generative AI, however, brings new capabilities that align directly with these needs. Specifically, large language models can assist in parsing complex systems, identifying functional components, and producing explicit structural mappings between analogs. This allows for more efficient analysis, explanation, and transfer of systems knowledge, while also supporting learners in recognizing meaningful analogies and avoiding superficial or misleading similarities.

4.3. Future Research Directions

The SALT framework offers a foundation for diverse future research directions spanning multiple methodological approaches, including field studies, experimental designs, and design-based research. To test the core propositions of SALT, we envision controlled experiments that present custom software tools that participants use to complete a task. The general experimental protocol would involve training participants to complete the task using a base system and then asking them to complete the same task using a new (target) system that differs from the base in specific ways (surface and structural). Such a protocol would provide flexibility to examine SALT predictions at all stages of the learning process. For example, do users automatically *access* their mental models of a base system to perform the same task, regardless of the apparent similarities of the systems? Do users attempt to *map* structural similarities between the systems even when surface features diverge? How do different mapping types lead to more or less successful performance, both on the target system and subsequent systems that support the same task?

Another potential approach involves case/field studies aimed at understanding how individuals learn new systems, focusing on the role of analogical reasoning in the learning process. Observations, focus groups, interviews, surveys, and think-aloud protocols are all techniques used to elicit and assess mental models (Hu & Twidale, 2023) and could be fruitfully applied to exploring the analogical learning process. This line of inquiry could be complemented by cognitive load assessments and the development of measurement frameworks to evaluate cognitive efficiency across different types of mental model formation. Additionally, field research could examine the integration of analogies into user documentation and support systems, assessing outcomes such as reductions in support ticket volume and improvements in user experience. Such research would enable a deeper exploration of the relationship between base and target system knowledge and the effectiveness of analogical reasoning when switching systems.

5. Conclusion

As information systems that support organizational work proliferate and evolve, the need for users to migrate and adapt to new systems to complete their tasks will continue to intensify. The learning processes employees experience during these transitions are a widely acknowledged but relatively under-theorized phenomenon in the IS literature, particularly relating to the effect of prior system knowledge. By framing system learning as an analogical process, the SALT model highlights the cognitive mechanisms through which users transfer—or misapply—prior system knowledge to new digital environments. This perspective opens new avenues for studying user adaptation, training effectiveness, interface design, and implementation outcomes. Future research can build on this foundation to examine the conditions that foster successful analogical transfer, mitigate negative learning, and support the development of resilient, transferable mental models across evolving technological ecosystems.

6. References

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