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Toward an Organizational Model of Change in Elementary Schools: The Contribution of Organizational Learning Mechanisms

Chen Schechter¹ and Mowafaq Qadach¹

Abstract

Purpose: This study explored a theoretical model that links teachers’ perceived uncertainty and teachers’ sense of collective efficacy with organizational learning mechanisms (OLMs) in elementary schools. OLMs serve as a mediator construct. Research Design: For testing the primary theoretical model, 801 teachers from 61 elementary schools (33 urban and 28 suburban) in Israel’s largest district responded to the research instruments. The authors used structural equation modeling to determine whether OLMs mediate between teachers’ perceived uncertainty and their sense of collective efficacy. Findings: A significant model, which included direct and indirect effects of teachers’ perceived uncertainty on teachers’ sense of collective efficacy, emerged for the urban school context. Although OLMs (storing, retrieving, and putting to use of information) served as a prominent mediating variable in the urban school context, OLMs did not play a mediating role in the research model for the suburban school context. Conclusions: This

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study strengthens the feasibility of the OLMs framework, based on information processing, to provide a concrete description of organizational learning processes in schools. The study provides a deeper understanding of how OLMs can serve as a significant link between the dynamic school environment and teachers’ attitudes, which may ultimately improve teachers’ work and students’ learning.

**Keywords**
organizational learning, organizational learning mechanisms, collective efficacy, uncertainty

Organizational learning has been conceptualized as a critical component in school change processes. Accumulating evidence indicates that higher performing schools function as learning organizations (Kruse, 2003; Silins & Mulford, 2002). Although the importance of organizational learning for the adoption of effective change is widely acknowledged (e.g., Giles & Hargreaves, 2006), the notion of organizational learning in schools is still murky and difficult to comprehend (Schechter, 2008; Fauske & Raybould, 2005; Marks & Louis, 1999; Stevenson, 2001). Despite the numerous conceptions of organizational learning in schools (e.g., coordinated group efforts, professional development programs, shared goals, active commitment to continuous improvement, horizontal network of information flow, open culture, teachers’ leadership), they are rarely translated into operational structures and processes in school reality (Fullan, 2000; Silins, Zarins, & Mulford, 2002). In this regard, Marks and Louis (1999) have correctly remarked that to serve as a prototype for effective change, organizational learning should be explored in a manner more conducive to empirical research and consequently to appropriate application in school settings; otherwise, organizational learning will surely become merely another theoretical fad. Thus, research should further examine how to translate this abstract concept into meaningful change processes in school reality.

This study is an attempt to explore organizational learning in schools through the conceptual framework of organizational learning mechanisms (OLMs), which focuses on gathering and assimilating information from both internal (organizational) experiences and external (environmental) changes, which lead to better internal adaptations (e.g., changes in structure, procedures, strategies; Ellis & Shpilberg, 2003; Lipshitz, Popper, & Friedman, 2002). In the absence of explicit intention and appropriate mechanisms, the potential for learning and change may be lost (Ghoshal, 1987). Hence, to
keep pace with a dynamic and uncertain environment, learning activities and processes should be developed that can both lead to new and diverse knowledge bases and nurture faculty’s shared belief in its capabilities.

In particular, the purpose of this study was to develop a theoretical model that would link teachers’ perceived uncertainty and teachers’ sense of collective efficacy with OLMs in elementary schools. In this study, OLMs serve as a mediator construct. Testing the primary theoretical model that describes the possible relations between the three research variables can help policy makers, superintendents, principals, and teachers to promote school learning and change. We turn next to the theoretical framework that guides our inquiry.

**Theoretical Framework and Hypotheses**

**Organizational Learning in Schools**

Organizational learning has been conceptualized as a critical component of school effectiveness, especially in view of the increasingly available information in societies today. As learning organizations, schools develop processes, strategies, and structures that enable them to learn and react effectively in uncertain and dynamic environments (Corcoran & Goertz, 1995; Fullan, 2000; Giles & Hargreaves, 2006; Kruse, 2003; Lipton & Melamede, 1997; Louis, 2006; Silins et al., 2002; Strain, 2000). In this regard, Louis (1994) and Kruse (2003) argued that schools’ capacity for innovation and reform relies on their ability to collectively process, understand, and apply knowledge about teaching and learning. This notion is supported by Spender and Grant’s (1996) criticism of the overemphasis in schools on what should be learned, instead of accentuating the processes of collective and continuous acquisition, creation, dissemination, and integration of knowledge. From an educational change perspective, Wohlstetter, Smyer, and Mohrman (1994) asserted that the major common element across actively restructuring schools is the extent to which they utilize collective learning mechanisms (e.g., circulating instructional reference materials and reports) that generate interactions among staff members around issues related to curriculum and instruction. Therefore, schools need to establish systemic structures and procedures for teachers to collectively think and share information on a sustained basis (Kruse, 2003; Silins & Mulford, 2002).

In line with the need to collectively think and share information in the context of accountability and school reform, data-driven decision making (DDDM) has become a central tenet in school improvement processes (Knapp, Swinnerton,
Copland, & Monpas-Huber, 2006). The education realm has adopted this concept from industry (total quality management, organizational learning), focusing on the use of multiple forms of data to drive continuous improvement at all levels of the organization (Halverson, Grigg, Prichett, & Thomas, 2005). In DDDM, data are collected to measure the effectiveness of organizational actions that lead into continuous cycle of data collection, evaluation, and synthesis through feedback loops (Danielian, 2009).

From the management science perspective (Easterby-Smith, 1997), organizational learning requires the existence of OLMs, which constitute concrete social arenas where knowledge can be analyzed and shared by individual members and then can become a property of the entire organization through dissemination and changes in standard routines and procedures. OLMs are institutionalized structural and procedural arrangements for collecting, disseminating, analyzing, storing, retrieving, and using information that is relevant to the performance of the organization and its members (Popper & Lipshitz, 1998, 2000; also see DiBella, Nevis, & Gould, 1996; Huber, 1991; Marquardt, 1996). Although the following five phases of the information processing (learning) cycle are listed in progressive order, learning is perceived as a cyclical, dynamic, and interactive process:

a. **Information acquisition: The process of obtaining knowledge.** This includes experiential learning (organizational experiments, organizational self-appraisal like action research), vicarious learning (in which organizations attempt to learn from other organizations’ strategies and technologies; e.g., external alliances), grafting (recruiting new members who possess knowledge that is not available to the organization), and searching and noticing the environment (e.g., scanning units; Dodgson, 1993).

b. **Information distribution: The process of sharing information that leads to understanding.** Information distribution expresses the process by which an organization shares information among its units and members (letters, memos, informal conversations, and reports), thereby promoting learning and producing new knowledge. In addition to traditional forms of information distribution such as telephone, facsimile, face-to-face meetings, and memorandums, there are computer-mediated communication systems, such as electronic mail, computerized conferencing systems, electronic meeting systems, document delivery systems, and workflow management systems. Thus, greater sharing or distribution of information leads to
greater organizational learning and can also lead to the creation of new knowledge (Argote, McEvily, & Reagans, 2003).

c. **Information interpretation:** A sociocognitive process that gives meaning to the distributed information. This occurs when organizations undertake sense making and information interpretation activities (Dodgson, 1993). These sense-making activities share and develop varied interpretations. This exchange of views and attitudes can transfer individuals’ tacit knowledge into organizational knowledge and assist in verifying, sorting, and filtering data from both inside and outside the organization (Nonaka & Takeuchi, 1995). Consequently, organizational members decide whether or not to incorporate the information into organizational routines. According to Zollo and Winter (2002), information can also be interpreted through knowledge articulation, which is the process through which implicit knowledge is articulated through collective discussions, debriefing sessions, and performance evaluation processes. By sharing their individual experiences and comparing their opinions with those of their colleagues, members can achieve an improved level of understanding of the causal mechanisms intervening between the actions required to execute a certain task and the performance outcomes produced.

d. **Organizational memory:** The processes and means by which organizational experiences are stored and coded into organizational memory for future use. These consist of both mental artifacts (e.g., stories that represent organizational cultural patterns and values) and structural-technological artifacts (e.g., resource room, written policies, dress, furniture, operating procedures) within an organization (Kruse, 2003; Weick, 2000). Efforts aimed at the preservation of organizational knowledge can also be described as either organic or constructed (Johnson, 1993). Organic memory includes individual organization members’ memories, the embedded memory resulting from organizational culture, standard operating procedures, expected role behaviors, and environmental factors. Constructed memory consists of knowledge stored in facilities deliberately designed and maintained for purposes of organizational memory. Such facilities include electronic databases, transaction records, and historic archives.

Fauske and Raybould (2005), however, conceptualized organizational memory as primarily consisting of mental information. They used the concept of mental models to explain how organizational memory operates. Memories
exist in individuals, and individuals who participate in an organization also may have shared knowledge and experience, which may also result in shared memories. Such collections of memories, which guide responses and interconnect around specific experiences, are called mental models. These mental models function by activating memories and responses that were previously developed to solve earlier problems or to address previous incidents. They include knowledge, assumptions, beliefs, values, and norms that guide behaviors and actions. It seems likely that as more people have accessibility to an organizational memory, organizational learning increases. Also, as more people can potentially update an organizational memory, there is a greater potential for organizational learning and change (Goodman & Darr, 1998).

e. Retrieving information from memory for organizational use: Organizational members draw on the encoded information to guide their decisions and actions. That is, past encoded information is used to influence present decision-making processes (Kruse, 2003). For example, staff meetings make use of summary reports of previous meetings; likewise, previous reports about learning and teaching are used for evaluative purposes. Effective use of data by school personnel has become a central tenet in school improvement processes, especially to raise test scores, reduce the achievement gap, and change school culture (Hamilton, Stecher, & Klein, 2002; Wayman, Brewer, & Stringfield, 2009). Research findings have linked data use to changes in school culture and teacher practices that result in improved student performance (Dantow, Park, & Wohlstetter, 2007; Kerr, Marsh, Ikemoto, Darilek, & Barney, 2006). Nevertheless, although scholars note the importance of educators’ expertise in using data to inform actions, educators’ ability to apply data has been described as inadequate (e.g., Wayman et al., 2009).

As with any conceptualization, limitations and critiques can be directed at the OLMs analytical framework: Whose interests are being served by extensively using OLMs? Does organizational information processing help to secure the hegemony of the administration? Can OLMs encompass not only knowledge that can be communicated through dialogue but also more implicit knowledge, such as intuition and nonverbal communication? Can learning be shaped only through conscious rational communication? Do OLMs assume that information processing can be free from coercion or deception? Can OLMs be used against colleagues, prompting mistrust of data use, especially in the context of high-stakes accountability (Heritage &
Yeagley, 2005)? Do OLMs represent an organizational-centered philosophy at the expense of the worker’s needs (Fenwick, 1997)? How can the development of the individual be integrated with promoting organizational shared identity through OLMs? Can formal channels of information processing (vs. informal ones) be conducive in an environment with high levels of uncertainty and changeability?

Perceived Uncertainty and Its Relations With OLMs

Despite the long history of uncertainty research, there is no single accepted model of perceived uncertainty (Ellis & Shpilberg, 2003). Uncertainty was defined by Galbraith (1974) as the gap between knowledge that the organization has already acquired and the knowledge required to carry out its assignments. Daft, Sormunem, and Parks (1988) defined uncertainty as the gap between the wanted information and the found information concerning the organization and its surroundings. More specifically, uncertainty is a result of a lack of information regarding environmental factors, not knowing the outcome of a decision and its losses if incorrect, and inability to assign probabilities to environmental factors (Duncan, 1972).

Almor, Ellis, and Shenkar (1997) suggest two major environmental dimensions influencing workers’ sense of uncertainty: (a) environmental complexity, various numbers of factors and the diversity of factors that influence the sense of uncertainty, and (b) environmental changeability, changes in the system properties that stimulate the sense of uncertainty (e.g., degree, pace, and consistency). In this regard, Duncan (1972) proposed that perceived uncertainty is composed of a simplicity–complexity dimension and a static–dynamic dimension. Complexity refers to the number of environmental elements and the level of interdependence among them, whereas dynamic (changeability) refers to the rate of changes in the environment, which are in a continuous process of change. He claimed that the dynamic dimension (changeability) contributes most to the sense of uncertainty and is a primary source of uncertainty for managers who are responsible for identifying opportunities and threats facing their organizations. Ellis and Shpilberg (2003), who used the complexity–changeability dimensions of perceived uncertainty in studies of Israeli business managers, reported that the changeability dimension, rather than the complexity dimension, predicted the extensiveness of organizational learning processes.

Dodgson (1993) argued that organizations need to learn to adapt to the uncertain environment and to improve performance, whereas Pavitt (1991) described organizational learning as a response to the need for adjustment in
times of great uncertainty. To adjust to changing environments and to make appropriate strategic choices, organizations must become aware of the ongoing environmental changes (Hall & Saias, 1989) and make sense of the environment (Daft & Weick, 1984; Weick, 2000).

Perceived uncertainty is presumed to be negatively related to the extent of OLMs in schools. As external environment influences organizational structures and processes (Daft & Weick, 1984), schools, which are open systems, need to interpret ambiguous and uncertain external events by developing information processing mechanisms. This relation is reflected in Galbraith’s (1974) assertion that “as the amount of uncertainty increases . . . the organization must adopt integrating mechanisms, which increase its information processing capabilities” (p. 29), consequently lowering faculty members’ sense of uncertainty. Thus, organizations establish OLMs that allow members to interpret information and share their views and attitudes to make their environment more predictable, thereby reducing members’ perceived uncertainty.

The negative relations between the OLM dimensions and phases and perceived uncertainty were supported by a study on project managers from the business sector (Ellis & Shpilberg, 2003), which found the intensity of usage for each OLMs phase (information dissemination, information gathering, information storage, and retrieval) to be negatively associated with perceived environmental uncertainty. Furthermore, these correlations were higher in the organizations that functioned under uncertain as opposed to certain environments. Thus, organizations operating in uncertain environments differed from organizations in relatively certain environments in their intensity of using learning procedures. The research literature in the education realm includes very few studies on perceived uncertainty, most of them relating to communication as a major factor in reducing uncertainty. For example, Antelo and Ovando (1993) found that site-based management is a viable strategy for coping with and reducing environmental uncertainty, mostly because of the incorporation of staff members in the decision making process. Moreover, Geijsel, Sleegers, Van den Berg, and Kelchtermans (2001) found a negative relation between secondary vocational education teachers’ sense of uncertainty and professional development activities.

With this said, we assume that as school members perceive their school as operating within a dynamic and uncertain environment, OLMs will be implemented to reduce members’ sense of uncertainty. In light of the above, the first assumption with regard to the variables was the following:

Hypothesis 1: The extent of teachers’ use of OLMs will be negatively associated with teachers’ perceived uncertainty.
Collective Efficacy and Its Relations With OLMs

Collective efficacy (CE) is defined as the “group’s shared belief in its conjoint capabilities to organize and execute the courses of action required to produce given levels of attainments” (Bandura, 1997, p. 477). CE can also be defined as a belief system that includes the mutual recognition of the various agents (e.g., home, school, and community) that each unit has a valuable and distinctive role in promoting success and together—and only together—do they have the capabilities to create environments conducive for the optimal development of the student. (Henderson, Jones, & Self, 1998, p. 4)

Thus, collective teacher efficacy is the perceptions of teachers in a specific school that the faculty as a whole can execute courses of action required to positively affect student achievement (Goddard, Hoy, & Woolfolk Hoy, 2000). Collective teacher efficacy is a characteristic of schools as experienced by teachers. Similar to the notion of OLMs, collective teacher efficacy is a “property” of the school that has emerged as a significant factor in school productivity (Goddard, Hoy, & Woolfolk Hoy, 2004). In this regard, teachers’ CE was shown to powerfully influence how teachers instruct students, motivate students, and manage their classrooms (Goddard & Goddard, 2001). Thus, strong CE beliefs can improve the effectiveness of teachers’ work as they modify the nature and practices of their organizations.

Schools are interactive social systems in which teachers collect, analyze, and share information that influences the social environment of the school (Bandura, 1993). In this regard, according to Walsh and Ungson (1991), when schools incorporate and intensely use information processing mechanisms, they develop and sustain a collective memory (causal maps, strategies) that can nurture faculty’s shared sense of efficacy. Hiatt-Michael (2001) suggested that the degree to which schools function as learning organizations not only may influence the willingness of school employees to embrace new innovations for promoting student achievement but also may nurture their personal well-being, their sense of efficacy in working with students, their work satisfaction, and their evaluation of the school as a high-performing organization.

Collective teacher efficacy powerfully influences the social norms of a school, increasing levels of health and climate of the school (Goddard et al., 2004). With this said, we expected teachers’ collaborative learning to influence efficacy beliefs, contributing to lower rates of suspension and dropping
out while increasing school orderliness (Esselman & Moore, 1992). To illustrate, in studies conducted in elementary schools (Schechter, 2008) and secondary schools (Schechter & Atarchi, under review), OLMs were significantly and positively (moderate to high) related to CE for student discipline (e.g., How well can teachers in your school respond to defiant students?). In light of the above, the second assumption of the current study was the following:

**Hypothesis 2:** The extent of teachers’ use of OLMs will be positively associated with teachers’ sense of CE.

### Urban and Suburban School Contexts and Study Variables

Schools do not operate in a vacuum; they function as part of a larger social system, including the school district and the local community in which they are embedded (e.g., Rumberger, 2004). The nature of the interface between schools and the larger system must be assessed, especially those exchanges that either foster or hamper the efforts made by schools to function in new and creative ways. Furthermore, this school–environment interface requires assessment in light of the aforementioned need for schools to operate as learning organizations to adapt to the uncertainty arising from interactions with the environment. In this regard, urban schools may be considered as working in a more turbulent, uncertain environment, whereas suburban schools may be considered as working in a more placid, certain environment (Hoy & Miskel, 2008). Indeed, teachers working in urban schools were found to perceive more extensive use of information processing mechanisms than staff from suburban schools (Schechter, 2007). Similarly, Klein (2000) reported that secondary schools in highly competitive and uncertain urban contexts used information processing mechanisms more extensively than secondary schools in relatively less competitive and more certain environments (suburban and rural contexts).

In the Israeli educational context, significant differences emerged between urban and suburban elementary schools in teachers’ sense of CE, with urban teachers demonstrating higher CE beliefs (Schechter & Tschannen-Moran, 2006). A possible explanation of this finding is that the urban schools had already adapted to their more competitive and uncertain environment (e.g., open enrollment zones) with improved performance and consequently held stronger CE beliefs. Suburban schools were only more recently exposed to this competitive and uncertain environment, thus perhaps increasing teachers’ perceived uncertainty and, in turn, diminishing their sense of CE. Therefore, one may assume that in the urban (uncertain) contexts, both direct relations and
indirect relations (through OLMs) may develop between teachers’ perceived uncertainty and teachers’ sense of CE, leading to the following hypothesis:

**Hypothesis 3:** Different patterns of effects among perceived uncertainty, OLMs, and CE will emerge: Israeli teachers’ perceived uncertainty will affect teachers’ sense of CE directly and indirectly among the urban schools’ group, with OLMs acting as a mediating construct, whereas in the suburban schools group only direct effects will emerge.

In view of the theoretical discussion and hypotheses, Figure 1 presents the basic research model, which graphically describes the expected theoretical connections among the aforementioned constructs.

**Israeli Educational Context**

The Israeli educational system is highly centralized in both structure and procedures (Iram & Schmida, 1998). According to this tradition of centralized education, the Ministry of Education controls schools in domains such as enrollment policy, writing and distributing curriculum materials, standards, testing, and hiring and firing of school staff (Gibton, Sabar, & Goldring, 2000). In this way, the Ministry of Education is the provider of education for all, geared toward matriculation exams that are mandatory for entrance into higher education institutions. All schools follow a basic national curriculum, although they can choose a specialty from a predetermined list of subjects (Oplatka, 2006). Schools can also conduct “experiments” under administrative direction from the ministry. In recent years, more open and flexible registration opportunities for schools (with weaker links between residential location and school attendance zones) have increased competition among schools. This has been coupled with relatively recent attempts (in the 1990s) to decentralize the school system through efforts such as school-based management, autonomous schools, and so forth. These processes occur much more frequently in urban schools, which operate in a relatively turbulent, highly competitive, and uncertain environment (open enrollment zones, school choice), compared to suburban schools, which operate in a relatively placid, less competitive environment.

**Method**

In this section, we explain the sampling and data collection procedures, variables, and analytical method used to test the hypotheses that guided the study.
Figure 1. The research model

Note. OLM = organizational learning mechanism; CE = teachers’ collective efficacy.

Sampling and Data Collection

To test the theoretical model, teachers from 61 elementary schools in Israel’s largest district provided the information for analysis. Although it was not possible to select a random sample of elementary schools in this district, we collected data from urban and suburban schools from diverse geographic areas. These schools represented the entire socioeconomic status range. More specifically, 33 (54%) of the participating schools were from urban environments, and 28 (46%) of the participating schools were located in suburban contexts. Only schools with a Grade 1–6 configuration and 15 or more faculty members were included in the sample. In each school, 15 teachers were chosen at random to respond to the research instruments. Of the teachers, 92% were females, with a mean of 9.91 years of classroom teaching experience at the current school ($SD = 3.53$), a mean of 14.11 years of classroom teaching experience overall ($SD = 4.35$), and an 85.3% workload ($SD = 8.61$),
calculated by dividing teachers’ mean weekly teaching hours by the full-time 30-hour workload for elementary school teachers. These demographic characteristics resembled those found in other studies on elementary schools in Israel (e.g., Somech & Ron, 2006).

A research staff member (who was not a faculty member) typically collected the data at the schools, although in several cases a faculty member administered the instruments. In both cases, the data collector explained the study purpose in general terms, guaranteed anonymity, and stressed the importance of candid responses. Thus, we collected usable data from 801 teachers (87.5% response rate, predominantly because of incomplete responses), 429 from urban schools and 372 from suburban ones, yielding a mean sample size of approximately 13 teachers per school.

**Research Instruments**

Data for this study comprised self-report questionnaires to tap subjective perceptions and work attitudes. Despite the obvious weaknesses of the self-report method, mainly because it is subject to social desirability bias (Beretvas, Meyers, & Leite, 2002), it remains the best method of assessment of how employees feel about and view their work (Spector, 1994).

**Perceived uncertainty.** Van de Ven and Ferry’s (1980) six-item two-factor model survey of perceived uncertainty was rated by teachers along a 5-point Likert-type scale ranging from 1 (low uncertainty) to 5 (high uncertainty). Factor analysis of the six items (using principal components extraction, varimax rotation) yielded two subscales:

1. Uncertainty resulting from the level of change (dynamism) in a system’s properties, such as degree, pace, or consistency (three items; Cronbach’s α for internal consistency reliability = .70). Sample items included “How similar are the day-to-day solutions, problems, or issues you encounter in performing your major tasks?” and “How often do you follow the same methods or steps for doing your major tasks from day to day?” (see the appendix).

2. Uncertainty resulting from the complexity (diversity) of a system’s properties and thus the number of elements to be considered when making decisions and their heterogeneity (three items; α = .50). Sample items included “What percent of the time are you generally sure of what the outcome of work efforts will be?” and “How often do difficult problems arise in your work for which there are no immediate and apparent solutions?”
A coefficient alpha of .70 is generally perceived as the minimum recommended for using composite scales in statistical analysis (Nunnally & Bernstein, 1994). Similarly, George and Mallery (2003) suggest that Cronbach’s alpha be .70, which indicates an acceptable internal consistency of the items in the scale, whereas a Cronbach’s alpha of .50 indicates a poor internal consistency of the items in the scale. Therefore, the complexity component was excluded for the next statistical procedures. This statistical finding was supported by earlier research suggesting that the level of change in a system’s properties has the greatest contribution to employees’ perceived uncertainty, whereas the complexity of a system’s properties has less influence on employees’ sense of uncertainty in the organization (Almor et al., 1997; Duncan, 1972).

**Organizational learning mechanisms.** Teachers’ perceptions of OLMs were measured using a 27-item four-factor model survey for elementary schools (Schechter, 2008), rated along a 5-point Likert-type scale ranging from 1 (doesn’t exist) to 5 (exists extensively). Factor analysis of the 27 items (using principal components extraction, varimax rotation) yielded four factors (see the appendix):

1. **Analyzing information** (9 items; \( \alpha = .91 \)), referring to the process of giving meaning to incoming information through collective sense making. As a result, school members decide whether to incorporate the analyzed information into organizational routines. Sample items included “Staff meetings are held to discuss school goals” and “Teachers work together to modify subject matter for students.”

2. **Storing, retrieving, and putting to use of information** (10 items; \( \alpha = .89 \)), referring to the processes and means by which organizational experiences are stored and coded into school memory. Concurrently, school personnel draw on the encoded information to guide their decisions and actions. Sample items included “Each curriculum/project has an updated instructional file” and “Staff meetings make use of summary reports of previous meetings.”

3. **Receiving and disseminating information** (5 items; \( \alpha = .85 \)), referring to the process in which school personnel are provided with information as well as share information with various school stakeholders. Sample items included “Reports about professional changes and innovations are circulated” and “There is a supply of professional and pedagogical reference materials.”

4. **Seeking information** (3 items; \( \alpha = .74 \)), referring to the process of actively searching for information. Faculty members attempt to learn from the strategies and technologies of other organizations.
(environmental scanning) as well as by gathering information from colleagues at their own schools. Sample items included “Teachers observe other teachers’ lessons for learning purposes” and “There are professional learning linkages with other schools.”

Collective efficacy. Tschannen-Moran and Barr’s (2004) 12-item two-factor model survey was used to measure teachers’ perceptions of the collective, rather than their personal beliefs about their own individual efficacy, rated along a 5-point Likert-type scale ranging from 1 (nothing) to 5 (a great deal). Factor analysis of the 12 items (using principal components extraction, varimax rotation) yielded two factors (see the appendix):

1. CE for instructional strategies (6 items; $\alpha = .83$). Sample items included “How much can teachers in your school do to produce meaningful student learning?” and “How much can teachers in your school do to promote deep understanding of academic concepts?”

2. CE for student discipline (6 items; $\alpha = .82$). Sample items included “How well can teachers in your school respond to defiant students?” and “How much can school personnel in your school do to control disruptive behavior?”

Data Analysis

As both the OLM and CE constructs reflect the school level, the appropriate analytic focus is the school (Sirotnik, 1980) rather than the individual teacher. Thus, individual responses were aggregated for each instrument (OLMs, CE, perceived uncertainty) at the school level (Hoy, Tarter, & Kottkamp, 1991). In other words, a between-school analysis (taking the school as the unit of analysis) served as the appropriate analytical focus (the aggregation followed these steps: computing the mean of each item for each scale to all teachers per school, computing the mean of the items for each subscale, aggregating the means to the school level, and aggregating the means at the school level). Nevertheless, it was critical to demonstrate high within-group agreement to justify using the teachers’ average as an indicator of a school-level variable (James, Demaree, & Wolf, 1993).

In this study, the OLM subscales did not significantly correlate with the demographic variables examined, including the teachers’ workload and their current and overall length of teaching experience. Moreover, more than 90% of teachers in these elementary schools were women. Hence, these demographic characteristics did not serve as control variables in this study’s analyses.
To test the study hypotheses, we analyzed the data in the following steps: First, we performed Cohen’s $d$ effect size analyses to determine whether school context differences (urban or suburban) would emerge with regard to the research variables. In the second step, we produced two different correlation matrices, one for urban schools and one for suburban schools. In the third step, we employed structural equation modeling (SEM) to find the best-fit model, that is, to determine which OLMs may mediate between teachers’ perceived uncertainty (because of level of change) and teachers’ sense of CE. SEM is especially well suited for analysis of data in the social and behavioral sciences because it allows testing of theoretical models by describing relations among several endogenous factors simultaneously (Klem, 2000). Thus, SEM is suitable for testing whether the hypothesized measurement model fits the data, allowing for both direct and indirect effects in the examination of causal pathways (Byrne, 2001; Ream & Palardy, 2008). To test the fit of the proposed theoretical model and the possible relations between the research variables, we used the AMOS 15.0 software program.

Furthermore, SEM consists of a set of linear equations that simultaneously test two or more relationships among directly observable and/or unmeasured latent variables (Shook, Ketchen, Hult, & Kacmar, 2004). Thus, SEM specifies hypothesized associations between the latent curves and other measured variables (see studies that have used both latent and observed variables in SEM models: Brouwers & Tomic, 2000; DeGarmo & Martinez, 2006; Salleh & Albion, 2004). In the current study, as information processing is a cyclical, dynamic, and interactive construct, OLMs were depicted as a unidimensional latent construct rather than a multifaceted one, whereas both perceived uncertainty and CE were measured as directly observed variables.

To test the third hypothesis, we adopted Kenny, Kashy, and Bolger’s (1998) causal step approach. By this approach, four criteria need to be met to support mediated relations: First, the independent variables must be related to the mediators. Second, the independent variables must be related to the dependent variables. Third, the mediators must be related to the dependent variables, with the independent variables included in the model. Fourth, mediation is considered full if the relations between the independent variables and the dependent variables are no longer significant in the presence of the mediator. When the relations are reduced but still significant in the presence of the mediator, this provides evidence of partial mediation. This four-step evaluation process is one of the most commonly used procedures to test a mediation effect (MacKinnon, Lockwood, & Williams, 2004).
Results

We tested whether aggregation was appropriate using both the \( rwg \) statistic (James et al., 1993) and ICC(1) and ICC(2) coefficients (Bliese, 2000). Faculty members’ perceptions of their work environment must coincide to support a claim that a construct composes an organizational level variable (Bliese, 2000). An \( rwg \) value of .70 or greater was suggested as a sufficiently “good” amount of within-group interrater agreement (James et al., 1993). In the current study, all scales exceeded this level, except for the OLM information seeking subscale (see Table 1). Values of \( rwg \) for the OLMs were .86 for analyzing information, .77 for storing, retrieving, and putting to use of information, .72 for receiving and disseminating information, and .52 for seeking information. Values of \( rwg \) for the other variables were .79 for uncertainty due to change, .92 for CE for instructional strategies, and .91 for CE for student discipline. These results provided sufficient statistical justification for aggregating individual responses into a school level score (see Bliese, 2000).

The within-group agreement was also evaluated by two measures. The interclass correlation coefficient 1 (ICC1) examines the within-group variance by answering the following question: “To what extent can variability in the measure be predicted from organization membership?” The interclass correlation coefficient 2 (ICC2) examines the between-group variance by answering the following question: “How reliable are the organization means within a sample?” (Bliese & Halverson, 1996). Values were ICC1 = .13 and ICC2 = .69 for receiving and disseminating information, ICC1 = .16 and ICC2 = .72 for storing, retrieving, and putting to use of information, ICC1 = .17 and ICC2 = .74 for seeking information, ICC1 = .41 and ICC2 = .90 for analyzing information, ICC1 = .07 and ICC2 = .51 for uncertainty due to change, ICC1 = .11 and ICC2 = .68 for CE for instructional strategies, and ICC1 = .21 and ICC2 = .78 for CE for student discipline. Bliese (2000) indicated that ICC1 generally ranges from 0 to .50 with a median of .12. In the current study, most values slightly deviated from the proposed median score.

There were significant differences in all scores (except receiving and disseminating information) between the urban and the suburban school contexts. The Cohen’s \( d \) effect size analyses of the research variables indicated that the urban school scores were substantially higher (except seeking information) than the suburban school scores (see Table 1). Hence, for the next steps of analysis, we treated the participating schools as two separate groups: urban and suburban.
Table 1. Within-Group Interrater Agreements, Means, Standard Deviations and Cohen’s $d$ Effect Sizes of Urban ($n = 33$) and Suburban ($n = 28$) Schools

<table>
<thead>
<tr>
<th>Variable</th>
<th>$r_{wg}$</th>
<th>Context</th>
<th>$M$</th>
<th>$SD$</th>
<th>$p$ Value</th>
<th>Cohen’s $d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organizational learning mechanisms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Analyzing information</td>
<td>.86</td>
<td>Suburban</td>
<td>3.51</td>
<td>0.64</td>
<td>***</td>
<td>−1.45</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>4.27</td>
<td>0.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Storing, retrieving, and putting to use of information</td>
<td>.77</td>
<td>Suburban</td>
<td>3.39</td>
<td>0.33</td>
<td>***</td>
<td>−0.86</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>3.75</td>
<td>0.49</td>
<td></td>
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</tr>
<tr>
<td>Receiving and disseminating information</td>
<td>.72</td>
<td>Suburban</td>
<td>3.19</td>
<td>0.39</td>
<td></td>
<td>−0.23</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>3.29</td>
<td>0.46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seeking information</td>
<td>.52</td>
<td>Suburban</td>
<td>2.69</td>
<td>0.53</td>
<td>*</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>2.36</td>
<td>0.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Organizational learning mechanisms</td>
<td></td>
<td>Suburban</td>
<td>3.20</td>
<td>0.33</td>
<td>*</td>
<td>−0.61</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>3.42</td>
<td>0.38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uncertainty due to change in system’s characteris</td>
<td>.79</td>
<td>Suburban</td>
<td>2.49</td>
<td>0.29</td>
<td>*</td>
<td>−0.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>2.60</td>
<td>0.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collective efficacy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE for instructional strategies</td>
<td>.92</td>
<td>Suburban</td>
<td>3.63</td>
<td>0.39</td>
<td>***</td>
<td>−1.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>4.16</td>
<td>0.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CE for student discipline</td>
<td>.91</td>
<td>Suburban</td>
<td>3.63</td>
<td>0.35</td>
<td>***</td>
<td>−1.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Urban</td>
<td>4.07</td>
<td>0.32</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. The $r_{wg}$ statistic represents reliability within schools averaged across all schools (James, Demaree, & Wolf, 1993). Cohen’s $d$ effect size was calculated as the ratio between (suburban school means minus urban school means) and (the mean $SD$ of urban schools and suburban schools). 

* $p < .05$; *** $p < .001$.

To test Hypotheses 1 and 2, we computed intercorrelations among all the study variables, separately for urban and suburban schools, as seen in Tables 2 and 3. In the urban group, the two CE subscales revealed significant positive correlations with all of the OLM subscales except the information seeking subscale and the uncertainty (due to change) subscale. A significant positive correlation also emerged between perceived uncertainty (due to change) and the OLM storing, retrieving, and putting to use of information subscale. A
<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>Organizational learning mechanisms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Analyzing information</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Storing, retrieving and putting to use of information</td>
<td>.82**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Receiving and disseminating information</td>
<td>.51**</td>
<td>.75**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Seeking information</td>
<td>.16</td>
<td>.44*</td>
<td>.62**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Due to change</td>
<td>.26</td>
<td>.38*</td>
<td>.22</td>
<td>.19</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collective efficacy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. For instructional strategies</td>
<td>.75**</td>
<td>.79**</td>
<td>.49**</td>
<td>.10</td>
<td>.45**</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>7. For student discipline</td>
<td>.74**</td>
<td>.79**</td>
<td>.62**</td>
<td>.28</td>
<td>.36*</td>
<td>.92**</td>
<td>1.00</td>
</tr>
</tbody>
</table>

*p < .05; **p < .01.
Table 3. Correlation Matrix for Suburban School Measures ($n = 28$)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Organizational learning</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mechanisms</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Analyzing information</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Storing, retrieving, and putting to use of information</td>
<td>.89**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Receiving and disseminating information</td>
<td>.57**</td>
<td>.63**</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Seeking information</td>
<td>−.26</td>
<td>−.08</td>
<td>.34</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Uncertainty</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Due to change</td>
<td>−.03</td>
<td>−.01</td>
<td>.28</td>
<td>.03</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Collective efficacy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. For instructional strategies</td>
<td>.88**</td>
<td>.78**</td>
<td>.50**</td>
<td>−.33</td>
<td>.05</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>7. For student discipline</td>
<td>.87**</td>
<td>.84**</td>
<td>.54**</td>
<td>−.18</td>
<td>−.04</td>
<td>.96**</td>
<td>1.00</td>
</tr>
</tbody>
</table>

$p < .05; **p < .01$. 
different pattern emerged in the suburban group: Although significant positive correlations emerged between the CE subscales and all OLM subscales except for information seeking, no significant correlations emerged between uncertainty (due to change) and the other research variables.

**Testing the Theoretical Model**

To test our theoretical model (Hypothesis 3), we developed a separate recursive path analysis model for each group (urban or suburban), according to the correlation matrix results that revealed different links among variables in the two school contexts. It is important to note that when we started running the proposed model for each group (urban or suburban), which includes the direct effect of perception of uncertainty (changeability) on OLMs, the model did not converge and we got a default model. Therefore, because of model-based problems, we dropped the direct effect of perception of uncertainty–change on OLMs (see Figures 2 and 3).

In line with the research hypothesis, the model for the urban schools fit their data better than the suburban schools’ model fit their data. The path coefficients for the urban context showed several overall model fit indicators for the suggested model: \( \chi^2(2, 33) = 0.551, p > .05 \), Bentler–Bonett normed fit index (NFI) = .99, comparative fit index (CFI) = .99, and root mean square error of approximation (RMSEA) = .00. All these procedures indicated that the proposed model constituted a plausible explanation, although this does not imply that it is the only possible model. An examination of a few other models derived from the correlation matrix indicates the superiority of the model presented.

As seen in Figure 2, the data gained from the urban schools fit the proposed model as follows: OLMs have a significant effect on CE for instructional strategies (\( \beta = .85, p < .001 \)) and on CE for student discipline (\( \beta = .88, p < .001 \)). OLMs as a latent variable composed four prominent factors: storing, retrieving, and putting to use of information (\( \beta = .73, p < .001 \)), analyzing information (\( \beta = .74, p < .001 \)), receiving and disseminating information (\( \beta = .62, p < .001 \)), and, less so, seeking information (\( \beta = .16, p > .05 \)). Uncertainty due to change showed a direct effect on CE for instructional strategies (\( \beta = .45, p < .01 \)), a direct effect on CE for student discipline (\( \beta = .35, p < .05 \)), and a moderate, indirect effect on CE through OLMs as the effect of storing, retrieving, and putting to use of information was significant (\( \beta = .38, p < .05 \)). The overall model explained 96% of the variance in CE for instructional strategies and 90% of the variance in CE for student discipline.
As seen in Figure 3, in the suburban schools’ group, the model fit the data to a lesser extent: $\chi^2(2, 28) = 12.2, p < .01$, NFI = .94, CFI = .94, and RMSEA = .43. An examination of a few other models derived from the correlation matrix of this group indicated the superiority of the suggested model, even though it was not satisfactory. In the suburban context, the model showed no direct effects of uncertainty due to change on CE and also no significant indirect effects through any of the four OLM subscales. OLMs had a strong direct effect on both CE subscales (for instructional strategies and student discipline). The overall model explained 99% of the variance in CE for instructional strategies and 94% of the variance in CE for student discipline. Thus, the results were not as significant as in the urban school context.

To test out whether the proposed theoretical model can fit for the two data groups (urban or suburban), a further SEM step was performed. Thus, we
performed a further SEM step to compare the proposed model with the two data groups (urban or suburban), thereby examining the important role that context may play. This statistical technique to compare between two groups is called Mixture Modeling, which is discussed in the context of SEM by Arminger, Stein, and Wittenberg (1999), Hoshino (2001), Lee, Song, and Tang (2007), Loken (2004), Vermunt and Magidson (2005), and Zhu and Lee (2001), among others. To make this statistical procedure, we needed to define the two data sets: A = urban and B = suburban. Then, AMOS ran the model by treating it as two separate models. In this comparative SEM step, model fit
Table 4. Assessment of Model Fit for Urban, Suburban, and Urban–Suburban Models

<table>
<thead>
<tr>
<th>Fit</th>
<th>Measurement for Urban Model</th>
<th>Measurement for Suburban Model</th>
<th>Measurement for Urban Versus Suburban Model</th>
<th>Recommended Values for Acceptable Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chi-square (χ²)</td>
<td>0.551</td>
<td>12.2</td>
<td>32.7445</td>
<td>Small chi-square</td>
</tr>
<tr>
<td>p Value of a chi-square probability</td>
<td>.759</td>
<td>.002</td>
<td>.003</td>
<td>Nonsignificant, p &gt; .05</td>
</tr>
<tr>
<td>Normed fit index (NFI)</td>
<td>.997</td>
<td>.943</td>
<td>.923</td>
<td>&gt; .9</td>
</tr>
<tr>
<td>Root mean square error of approximation (RMSEA)</td>
<td>.000</td>
<td>.435</td>
<td>.151</td>
<td>&lt; .08</td>
</tr>
</tbody>
</table>

Note. Chi-square probability value greater than 0.05 indicates acceptable model fit. The p value of the model presents the proximity between the calculated model according to the data set and the estimated hypothetical model and therefore should not be significant. For NFI (also known as the Bentler–Bonett normed fit index), 1 = perfect fit. NFI values greater than .95 are good, those between .90 and .95 are acceptable, and those less than .90 indicate a need to respecify the model. RMSEA values less than .05 indicate good fit, those of .00 indicate exact fit, those from .08 to .10 indicate mediocre fit, and those greater than .10 indicate poor fit.

indicators were as follows: χ²(2, 33, 28) = 32.7445, p = .003, NFI = .923, and RMSEA = .151. Most of the goodness-of-fit indices are not acceptable, indicating that the comparison model between the urban and suburban contexts is not appropriate for the two data sets. For a full description, see Table 4.

A significant correlation was found between the independent variable of uncertainty–change and the OLM subscale of storing, retrieving, and putting to use of information (see Figure 2). Therefore, mediation analysis tested whether the relations between uncertainty due to change and CE were partly the result of a mediation effect of the OLM subscale of storing, retrieving, and putting to use of information. To test for mediation, we adopted Kenny et al.’s (1998) causal step approach to test for mediation effects (MacKinnon et al., 2004). Using this approach, as seen in Figure 4, four criteria were met to support mediated relations: Findings pertaining to the first criterion in the mediation analysis indicated a significant positive correlation between uncertainty due to change and storing, retrieving, and putting to use of information (β = .38, p < .05). The second criterion in the mediation analysis revealed significant
positive correlations between uncertainty due to change and the dependent variables: CE for instructional strategies ($\beta = .45, p < .01$) and CE for student discipline ($\beta = .35, p < .05$). The third criterion in the mediation analysis revealed significant positive correlations between the mediator storing, retrieving, and putting to use of information and the dependent variables (CE for instructional strategies and CE for student discipline) and between the mediator storing, retrieving, and putting to use of information and the independent variable uncertainty due to change. Finally, testing for the fourth criterion of the mediation analysis (full or partial mediation) revealed nonsignificant relations between uncertainty due to change and CE for instructional strategies ($\beta = .06, p > .05$) and between uncertainty due to change and CE for student discipline ($\beta = .17, p > .05$), suggesting full mediation (see Figure 4).

**Discussion**

The results of the present study outlined distinctive patterns of relations between perceived uncertainty and OLMs. We expected to find a negative correlation between perceived uncertainty and the extent of OLM use in...
elementary schools. This assumption derived from previous studies, which have found that information processing reduces uncertainty and hence increases learning (Antelo & Ovando, 1993; Schechter, 2008; Ellis & Shpilberg, 2003; Mason, 1993). The SEM analyses did not support the first hypothesis. To the contrary, a positive significant correlation emerged between urban teachers’ perceived uncertainty (due to change) and their perceived use of the OLMs of storing, retrieving, and putting to use of information, whereas in the suburban model no significant correlations emerged. Thus, to adapt to the challenging urban environment, teachers seemed to institute and extensively utilize learning mechanisms of storing and retrieving information, thus enriching their corporate memory.

The SEM analyses for predicting teachers’ CE revealed that in both contexts (urban or suburban) OLMs played an important role. More specifically, the results indicated a positive and large direct effect of OLMs (as a latent variable) on CE, in both the urban and the suburban schools. This finding is consistent with recent empirical studies that have revealed significant positive relations between collaborative learning and teachers’ sense of CE (e.g., Schechter, 2008; Bowen, Ware, Roderick, & Powers, 2007), thus supporting the second hypothesis.

The results of the present study depicted distinctive patterns of relations between perceived uncertainty and CE. In the urban context, positive significant correlations emerged between uncertainty due to change in the system’s properties and both subscales of CE, whereas in the suburban context no significant correlations emerged between uncertainty and CE. When we tested the research model for urban schools, the findings attested to the central role of OLMs (storing, retrieving, and putting to use of information) in mediating the relations between teachers’ perceived uncertainty (due to change) and teachers’ sense of CE. On the other hand, OLMs did not play a significant mediating role in the research model for the suburban schools. A possible explanation for this important finding is that within the Israeli educational context, urban schools have been operating for years (since the 1990s) in a relatively highly competitive environment (open enrollment zones, school choice), whereas suburban schools have not encountered a strong need to operate in such a competitive environment. Therefore, in the urban context, schools have been under great pressure to adapt to the increased uncertainty and competition, thus employing OLMs that nurture their “school memory” and consequently raising teachers’ sense of CE. This is in line with data indicating that schools operating within competitive and high-stakes-accountability systems are more involved in DDDM processes than schools that do not operate within such educational systems (Marsh, Pane, & Hamilton, 2006).
Although the literature on organizational memory and remembering has been quite limited and underrepresented in the context of school change processes (Kruse, 2003), the suggested model in this study depicted the importance of storing, retrieving, and putting to use of information. In this regard, information overload—collecting information without sufficient mechanisms for storing it in organizational memory—increases the risk of being unable to comprehend the information or use it effectively in decision-making processes (Feldman & March, 1981). Put differently, information gathering alone is not sufficient for reducing uncertainty when organizations lack the right mechanisms for incorporating the information into organizational memory and retrieving this valuable information for future organizational use (Daft & Weick, 1984).

With regard to future research, the study’s findings suggest that it is worthwhile to investigate schools’ information processing by dividing the OLM construct into its subscales. Despite the conceptual interrelatedness of the OLM dimensions and phases, OLMs are better depicted as a multifaceted construct rather than a unidimensional one. Thus, future theoretical hypotheses and models need to consider OLM subscales, their interrelatedness, and their balance during usage within schools. On a similar note, whereas in the urban school context the information-seeking dimension significantly correlated with two other OLM dimensions (receiving and disseminating information; storing, retrieving, and putting to use of information), in the suburban school context seeking information was unrelated to any of the other OLM dimensions. As the educational contexts of urban and suburban schools vary greatly (turbulent vs. placid environments), it may be useful to develop an OLM subscale for the suburban school context.

The focus of this study was elementary schools. Elementary schools are generally much smaller than middle and secondary schools and therefore may incorporate processes of collective information processing more easily. Middle and especially secondary schools, however, place greater emphasis on subject-matter-oriented specialization and division of labor, hindering the schools’ capacity for creating and sustaining collaborative learning. Thus, further analyses should assess whether and how the school-level configuration plays a role in developing collective learning mechanisms and especially in developing school memory. How do subject-matter teams (e.g., math) construct their own memory? What are the unique characteristics of each subject matter’s memory? What are the effects of these unique “memories” on student learning? How do these subject-matter memories interact with one another, thus affecting other memories and being affected by them?
Organizational and school memory needs to be accompanied with effective channels for retrieving information. With this said, what kinds of information influence practitioners’ ability to retrieve and exploit the information and then incorporate it in their practices? What kinds of information can be effectively retrieved immediately after codification in organizational memory (short-term memory) and after a long period of time since codification in organizational memory (long-term memory)? What are the contextual school characteristics that affect the ability of school members to learn from the stored information and then use it in their daily practices?

Although this research contributes to understanding the suggested model’s relations, further study is needed to develop an integrative model that includes both teachers and administrators who work in schools with varying uncertainty levels, regarding OLMs and CE. Moreover, longitudinal explorations would be worthwhile to more holistically take into consideration the issue of timing and enable testing of possible trends affected by changing levels of practitioners’ perceived uncertainty. For example, conceivably, teachers and administrators of newly established or developing schools may use learning mechanisms more extensively than faculties of well-established schools to cope with their uncertain context, consequently increasing the faculty’s joint belief in its ability to improve student learning.

Finally, it is important to note several limitations of the current study. First, the available data from each elementary school were supplied by approximately 13 teachers, a small number that leads to questioning of the aggregation of the research variables to reliably represent school characteristics. Although we tested the variation in participants’ perceptions as a means of deciding whether it was reasonable to aggregate the data to the school level, this aggregation should be perceived as a proxy of what in reality are much more complicated sets of relationships within schools. Second, the self-reported study instruments could have been influenced by social desirability responding, endangering the “trueness” of the study findings. Therefore, further research should use other measures (e.g., direct observations, in-depth interviews) for evaluating the research constructs (OLMs, CE, perceived uncertainty) as qualities of schools. Third, the results suggest a marginally significant path from perceived uncertainty to storing, retrieving, and putting to use of information ($\beta = .38, p < .05$), calling for further research on school memory in the context of accountability systems. Fourth, OLMs, as conceptualized in this study, are formal channels of information processing, thus overlooking many informal learning mechanisms used in schools. Further research needs to qualitatively explore how informal learning mechanisms are formalized over time by the group of learners and how informal
and formal learning mechanisms are used in times of environmental uncertainty. Fifth, it is difficult to measure perceived uncertainty clearly and reliably. The perceived uncertainty questionnaire utilized here was not developed for the educational realm; therefore, possibly, a better matched questionnaire based on the reality of schools might yield more accurate results pertaining to teachers’ sense of uncertainty.

Appendix

Perceived Uncertainty–Change (Dynamism)

How similar are the day-to-day solutions, problems, or issues you encounter in performing your major tasks?
How often do you follow the same methods or steps for doing your major tasks from day to day?
During a normal week, how frequently do expectations arise in your work that require substantially different methods or procedures?

Analyzing Information

Teachers work together to plan educational activities.
Teachers work together on ways to improve the curriculum and instruction.
Staff meetings are held to discuss school goals.
Teachers work together to modify subject matter for students.
Discussion groups meet to deliberate on professional issues.
Meetings are held to evaluate students’ behavior.
Meetings are held to evaluate students’ academic achievements.
Meetings are held to decide on how the school evaluates student achievement and the curriculum.
Joint events/initiatives/projects are conducted with parents and other groups in the community.

Storing, Retrieving, and Putting to Use of Information

Staff meetings make use of summary reports of previous meetings.
Previous reports about learning and teaching are used for evaluative purposes.
Staff meetings make reference to decisions taken in previous meetings.
Appendix (continued)

Curriculum is modified on the basis of evaluative feedback. Information obtained while monitoring and evaluating school activities is implemented in planning future organizational activities. Instructional methods are modified on the basis of analysis and evaluation of school activities. Summary reports of school activities/projects are prepared. Summaries of teacher work/school projects are stored in a location accessible and known to everyone. There is a resource room where achievement reports, procedures, pedagogical material, and the like are stored and can be easily retrieved. Each curriculum/project has an updated instructional file.

Receiving and Disseminating Information

Reports about professional changes and innovations are circulated. Evaluation reports on school programs/projects are circulated. Periodic evaluation reports on school curriculum are circulated. There is a supply of professional and pedagogical reference materials. Professional literature (articles, books) about educational-pedagogical research is received.

Seeking Information

Teachers go over summaries (minutes) of staff meetings. Teachers observe other teachers’ lessons for learning purposes. There are professional learning linkages with other schools.

Collective Efficacy for Instructional Strategies

How much can teachers in your school do to produce meaningful student learning? How much can teachers in your school do to help students master complex content? How much can teachers in your school do to help students think critically? How much can teachers in your school do to promote deep understanding of academic concepts?
How much can your school do to foster student creativity?
How much can your school do to get students to believe they can do well in schoolwork?

**Collective Efficacy for Student Discipline**

How much can school personnel in your school do to control disruptive behavior?
How well can adults in your school get students to follow school rules?
How well can teachers in your school respond to defiant students?
How much can your school do to help students feel safe while they are at school?
To what extent can school personnel in your school establish rules and procedures that facilitate learning?
To what extent can teachers in your school make expectations clear about appropriate student behavior?

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**References**


Fenwick, T. J. (1997). Questioning the learning organization concept. In S. M. Scott, B. Spencer, & A. Thomas (Eds.), *Learning for life: Reading in Canadian adult education* (pp. 140-152). Toronto, Canada: Thompson.


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