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SYSTEM LIFE EXPECTANCY AND THE MAINTENANCE EFFORT: EXPLORING THEIR EQUILIBRATION[1]

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Abstract

Aging information systems are expensive to maintain and most are eventually retired and replaced. But what determines (in the choices made by managers) whether and when a system reaches end-of-life? What shapes managers' judgements about a system's remaining life expectancy and do these judgments influence the maintenance effort itself? System maintenance and prospective replacement are examined here in new terms, positing that managers "equilibrate" (balance) their allocation of maintenance effort with their expectations of a system's remaining life. Drawing from data on 758 systems among 54 organizations, support is found for an exploratory structural equation model in which the relationship between maintenance effort and remaining life expectancy is newly explained. A "portfolio effect," reflecting a system's familial complexity, is also found to be directly and positively related to the maintenance effort. A further finding is that a system's size is directly and positively associated with its remaining life expectancy. Notwithstanding normative research suggesting the contrary, larger systems may tend to be longer-lived than smaller systems. Practically, the suggestion is made that better documented and monitored portfolios, together with regular, periodic performance assessments, can lead to better management of systems' life cycles.

Keywords: Maintenance effort, life expectancy, systems replacement, familial complexity, structural equation modeling

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Introduction

Maintaining information systems in today's organizations is widely understood to be an accomplishment requiring substantial expended effort. Significant human resources are typically committed and the average IS organization now spends more time maintaining existing systems

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and their software than it does developing new ones (Hanna 1993; Martin and McClure 1983; Moad 1990; Nosek and Palvia 1990). Systems are also long-lived. In some organizations, systems outlive the tenures of the people who maintain and use them by a wide margin (Swanson and Beath 1989).

Systems are nevertheless subject to structural deterioration and obsolescence with age, and most are eventually retired and (usually) replaced. More than half of an organization's new systems development effort may now be allocated toward the development of replacement systems, rather than toward systems that expand the scope of the total systems family (Swanson and Beath 1989). Systems, therefore, have limited useful lives reflected at any one moment by their present age and expectations of their eventual retirement. All face expected end-of-life. Accordingly, some organizations periodically estimate and record their systems' remaining life expectancies.[2]

What determines (in the choices made by managers) whether and when a system will be retired and replaced in the organization? What shapes managers' judgments about a system's remaining useful life and do these judgments affect the maintenance effort itself? Can regular patterns of retirement and replacement be observed among firms? The practitioner literature provides informal observations based on selected reports from the field. Five reasons for retiring and replacing software have been presented (Zvegintzov 1984): (1) it is no longer needed; (2) it no longer runs on its hardware; (3) its hardware is replaced; (4) it is not adapted to changing real-world conditions; (5) superior alternative software is developed or is available for purchase. Another suggestion is that fourth-generation tools and application packages make replacement of older systems easier to cost-justify than in earlier years (McNurlin 1983). More recently, managers are reported to be replacing older systems as part of infrastructure overhauls and a widespread move toward client/server computing environments (Hanna 1993; Swanson 1996).

While research on maintenance is growing (Kemerer 1995), research on retirement and replacement is scant. Gode et al. (1990), building from the work of Barua and Mukhopadhyay (1989), develop an economic model of replacement timing which suggests that the optimal operational life of a system may decrease with an increase in initial system size. Chan et al. (1994, 1996) extend this model by relaxing the assumption of an instantaneous rewrite time, finding that initial system size should not affect optimal rewrite timing where returns to programming effort are constant to scale. Both modeling studies presume that the functionality of the replacement system is equivalent to that of the system being maintained. Sakthivel (1994) presents a model for deciding between maintaining existing software and replacing it with redeveloped software based on a comparative analysis of equivalent annual lifespan costs. Differences in functionality between the existing and replacement-candidate systems may in principle be incorporated in the analysis as opportunity costs. Notably, all of these works take a normative view. Their analyses are based primarily on models and their assumptions and implications, rather than on data from the field.

On the empirical research front, Swanson and Beath (1989) present 12 cases that suggest that replacement has become a common practice in software development. More than a half of all new systems under development in the 12 firms studied were replacement systems. Managers reported the systems being replaced averaged about twelve years in age and had become hard to use and maintain. In several instances, replacement also involved consolidation of multiple systems within the application portfolio, reminding us that a system's life may depend on other systems to which it is related. However, beyond such fragmentary reports as this, empirical research on retirement and replacement has been lacking. Whether system size or other characteristics are widely associated in practice with the timing of system replacement has not been systematically studied.

[2]Some one third of IS managers taking an executive education course at our university over recent years report that their organizations make these estimates. For reasons of self-selection, this proportion is no doubt high compared to the broad population.

This paper reports selected findings from an IS census offering new evidence and fresh insights into system life cycles in firms. Drawing from data on 758 systems among 54 organizations, we examine system maintenance and prospective replacement in new theoretical terms, positing that managers "equilibrate" (balance) their allocation of maintenance effort with their expectations of a system's remaining life. We incorporate this notion in an exploratory structural equation model and find this model well fitted to the data. We also find support for a "portfolio effect," in which the complexity of a system's familial ties directly and positively affects the maintenance effort. We find further that larger systems may be longer-lived than smaller systems, notwithstanding normative research suggesting the contrary.

The sections to follow elaborate. We first present preliminary theory. We then describe our method and data and present our analysis and findings. We discuss these findings and address their implications in a concluding section. Practically, we suggest that better documented and monitored portfolios, together with regular, periodic performance assessments, can lead to better management of systems' life cycles.

Exploratory Theory

The maintenance of information systems is classically understood as the last phase in a lengthy system developmental life cycle (Boehm 1981). Historically, development theory has focused more on design and implementation approaches for bringing a system to organizational life than it has on the care given to a system over its subsequent life course (Larsen 1998; Swanson 1988). Accordingly, the perspective on maintenance has often been backward-looking, with emphasis given to revisiting the earlier developmental phases and correcting their associated oversights and mistakes (via the feedback loop in the "waterfall model").

In our view, however, the effort to maintain systems in organizations may be better understood as *forward-looking and aimed at extending their useful lives.* Not insignificantly, the maintenance phase also parallels the usage phase of a system's life. Larsen describes how a system passes through three characteristic subphases of usage. It first undergoes a period of change anchoring in which users become accustomed to the system. In this phase, the maintenance effort is often aimed at shaking out remaining bugs and "plugging gaps" to meet reasonable user expectations. The system next enters a prolonged period of change refinement, where usage is largely well understood and accepted. Here the maintenance effort typically focuses on incremental enhancement following an established trajectory. Eventually, however, Larsen argues, a "gap between business needs and deliverables" will tend to appear and increase over time until a system reaches a change termination period in which its demise and substitution arise. Here the end of maintenance is foreseen. The present research explores the ramifications of this aging process and developmental sequence for management's assessment of life expectancy and for the associated effort in maintenance.

How, then, do systems age? They age much as all organizational infrastructure ages. Structure and integrity gradually erode (Banker et al. 1993; Lientz and Swanson 1980). Error-prone, patchwork solutions to new problems begin to prevail. Rational underpinnings are undermined as the assumptions on which the systems were built tend to become obsolete. While some of these assumptions pertain to the system's technology platform, others are based on the applications and their functionality and architecture. Significantly, users demand constant changes to systems and their functionality, largely in response to changing environments and needs different from original design assumptions (Lientz and Swanson 1980). Maintenance is typically in response to these demands. Eventually, however, aging systems come to be candidates for retirement and replacement, as maintenance becomes more problematic and new organizational solutions based on new assumptions are envisioned. New ideas percolate (Larsen 1998). Replacement systems offering substantially improved functionality and/or usability are conceived. As the end of any system's life is eventually foreseen, the maintenance effort itself may be moderated. In particular, certain enhancements desired by users may be foregone in anticipation of imminent retirement and replacement.

We suggest that management should be expected to "equilibrate" (balance) its allocation of system maintenance effort with its estimate of a system's remaining life. An increase in the maintenance effort may extend the system's estimated remaining life. However, the estimate of a shortened remaining life may call for a reduction of the system maintenance effort. Because the two variables are, in principle, intimately related in their determination, it seems reasonable that management should take each into account with respect to its decision or estimate of the other. This equilibration hypothesis is a principal working hypothesis of the research reported here. It follows very naturally, we believe, from the system aging and developmental process described above. Indeed, Larsen's "change termination" subphase of usage may be directly interpreted in equilibration terms.[3]

In this context, what factors are most likely to account for management's equilibrated allocation of effort in maintenance and its estimate of a system's remaining life expectancy? Among the likely groups of explanatory factors would be characteristics of the system itself, characteristics of the IS department and its staff, and characteristics of the broader using organization (Swanson and Beath 1989). Over the life of the system, change may be precipitated in the broader firm affecting its business scale, scope, and profitability with ramifications for the IS department and its mission, headcount, and budget, and for the functionality required of the system itself. Organizational context may thus explain significant aspects of management's attention to maintenance and a system's life course.

However, we are primarily interested in characteristics of systems themselves and, in particular, in basic "demographic" characteristics such as age, size, and familial association within a portfolio (McFarlan 1981; Swanson and Beath 1986). Such characteristics are fundamental to the study of life cycles of systems populations and, we shall argue, to assessment of a system's life expectancy in this context.

Among demographic characteristics of the system itself, *system age* is the most clearly implicated in the developmental process just described. It essentially accounts for the accumulated effects of system change over time and is naturally linked to life expectancy. Past research has shown that system age has an impact on the maintenance effort. Among other characteristics, *system size* is perhaps the most important as it is most directly associated with the scale of resources needed in both maintenance and prospective replacement. *It has also been the focus of past research*, including the scant prior work on replacement described above. In the present exploratory research, we will be particularly interested in the effects of system age and size, while controlling for several of the other likely explanatory factors.

We will further be especially interested in a third system characteristic not hitherto studied. While a conventional life cycle approach would address the life of a system largely in terms of its own "internal" aging and developmental process, we suggest a broader view leading to the third characteristic. We propose that management's equilibrated allocation of effort in maintenance and its estimate of a system's remaining life expectancy is likely to depend on more than the system's age, size, and other individual characteristics, in the context of whatever one-for-one replacement alternatives may be conceived. We note that the key architectural assumptions underpinning any system are rarely confined to the individual system itself. They characteristically extend to and from other systems within the organization. Thus, in prior research, Swanson and Beath (1989) found that the replacement process often involves a consolidation of systems

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[3]While from our perspective, the equilibration idea applies throughout a system's usage and maintenance, it clearly "bites" later in the life cycle rather than earlier, probably first becoming noticeable in change refinement as a prelude to change termination. Stinchcombe (1990) speculates that such incremental refinements become progressively less productive over time while serving narrower constituencies; perhaps this leads management to begin its moderation of the maintenance effort. It may also eventually trigger recognition of a growing performance gap calling for replacement.

within the larger systems family. For example, in one case, four new systems were to replace 12 within the organization (p. 99). Apparently, systems often originate, grow, and develop in relation to other systems in the family so as to eventually suggest absorption within an alternative, more integrated systems solution. More broadly, then, managers face a portfolio problem in the allocation of organizational resources to maintenance and new system development, with obvious ramifications for the decisions made about any one system.

In the present research, we accordingly also posit a *portfolio effect* on the effort devoted to system maintenance and on expectations as to a system's remaining useful life. We conjecture that systems will require more maintenance to the extent that they are related through their data to other systems in the family, reflecting their *familial complexity*. Systems may require more maintenance either because they must rely on other basis systems for their data, or because other dependent systems must rely in turn on them. We conjecture further that systems will require more maintenance to the extent that they link multiple business functions in the organization, reflecting their *business functional complexity*. Such complex systems and their data in effect mediate the mutual reliance of different business functions and their employees upon each other. In both situations, we suggest that *portfolio complexity* is added to the maintenance task beyond that which may be reflected in the amount and internal structure of the software code itself. In both situations, maintainers are faced with an increased communication and coordination task involving diverse users and other maintainers within the organization, which should extend their overall effort. Broadly then, we conceive a system's portfolio complexity to be the complexity of its coordination task relative to the larger task of the portfolio as a whole.

Drawing from these basic ideas, we present in Figure 1 an exploratory research model in which the maintenance effort and remaining life expectancy associated with a system constitute the two related dependent variables of interest. The system's age, size, and portfolio complexity constitute the independent variables hypothesized to significantly explain them. Consistent with the equilibration hypothesis, the dependent variables are further presumed to affect each other.[4] Overall, the model enables us to focus upon three principal questions: (1) Are system life expectancy and the maintenance effort likely related as suggested by the equilibration hypothesis? (2) Is there evidence of a portfolio effect upon these two possibly related dependent variables? (3) What are the effects of system age and size in this context?

While the exploratory model is admittedly highly confined, it does not lack for associated explanatory potential. Our set of three independent variables incorporates a rich set of likely related explanatory associations, summarized for convenience in Table 1. These associations serve as linkages in our overall reasoning. Moreover, while we do not portray it in our model, there exist likely cross-associations among the three variables, also indicated in Table 1, which must be taken into explanatory account.

Summarizing thus far, a basic premise of our exploratory model is that certain core demographic variables such as a system's age, size, and portfolio complexity are important in explaining management of a system's life course (Swanson and Beath 1986). They are important not just because management may take them into direct account, but because they are also fundamentally related to various key aspects of the maintenance task and, we conjecture, to prospective termination and replacement. Both directly and indirectly, they should be in some part predictive of managerial commitments.

[4]Strictly speaking, our model is nonrecursive as it incorporates a primitive causal feedback loop reflecting the hypothesized equilibration between the two dependent variables. In Figure 1, we nevertheless collapse this loop, rather than portraying the two component effects separately, because in the present research we will not attempt to examine the equilibration process in its particulars. Indeed, our present model does not allow for this, inasmuch as it incorporates no "instrument" variable presumed to be a cause of one of the two variables, but not the other (Cohen and Cohen 1983, p. 371).

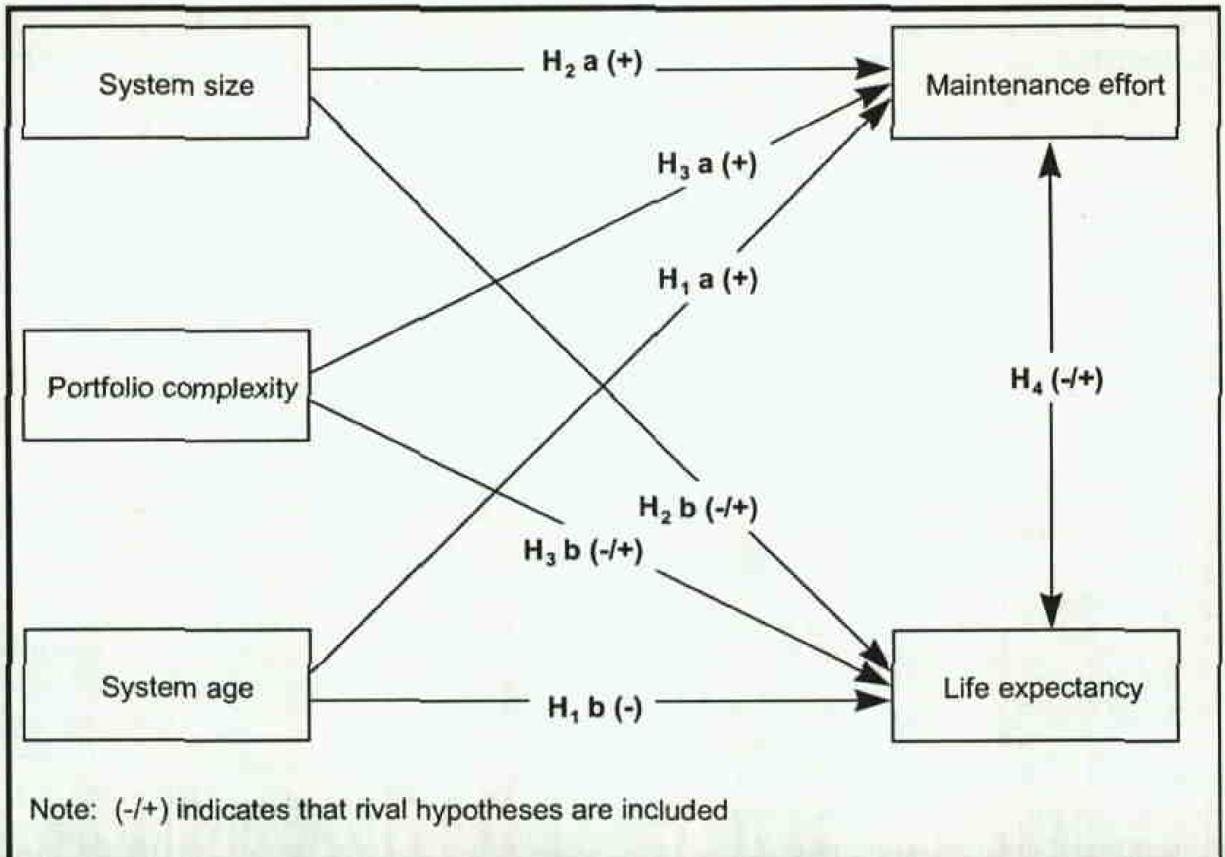

Figure 1. Research Model

We next turn our attention to the specific hypotheses associated with our model, drawing from and elaborating upon the posited explanatory associations summarized in Table 1. We consider the likely effects of each independent variable in turn upon the two dependent variables, followed by the likely effects of the two dependent variables upon each other. We offer four groups of hypotheses. In the case of several hypotheses specific to a system's remaining life expectancy, we discuss rival hypotheses as seem appropriate, consistent with the exploratory nature of the research. The hypotheses are summarized graphically in Figure 1.

We begin with system age and its effects, where the interpretations are relatively straightforward. In the case of the maintenance effort, we simply reassert for revalidation what has been found from earlier research (e.g., Lientz and Swanson 1980). *Age is a significant and positively associated* predictor, because, for example, older systems may come to be maintained by those unfamiliar with their original development and technology or for the other related reasons, summarized in Table 1. In the case of remaining life expectancy, younger systems should (obviously) tend to have more of it in that their underpinnings should be based on present technology and architectural assumptions and because the logic for replacing or terminating them would likely contradict the logic for their more recent establishment.[5] Thus:

(H1) Where the system's age is greater, (1) the maintenance effort is greater and (2) remaining life expectancy is lesser.

[5]Of course, our reasoning might not hold up if systems suffered in general from a high "infant mortality" rate and older systems were truly "immortal" (Zvegnintzov 1984). However, while many systems in the making are aborted when things go wrong, once new systems enter into production they tend to cling successfully to life, insofar as we know.

Table 1. Independent Variables and Related Explanatory Associations

Independent Variables	Related Explanatory Associations
Age	Older systems tend to be: • more structurally complex with substantial patchwork (Kemerer and Slaughter 1997; Vessey and Weber 1983). • less stable with modification (Brooks 1975; Kafura and Reddy 1987; Kemerer and Slaughter 1997; Lientz and Swanson 1980). • less familiar to their maintainers (Lientz and Swanson 1980; Swanson and Beath 1989). • built with older technology. • imbedded in older business processes. • (for these reasons) more difficult to maintain (Banker et al. 1993; Kemerer and Slaughter 1997; Lientz and Swanson 1980). • (for these reasons) more associated with a need to replace (Chan et al. 1994; Gode et al. 1993). Cross-associations: • Older systems tend to be larger with accumulated enhancements (Kemerer and Slaughter 1997; Lientz and Swanson 1980). • Older systems tend to be associated with greater portfolio complexity, accumulated over their enhancement history.
Size	Larger systems tend to: • be more structurally complex (Banker et al. 1993; Kemerer and Slaughter 1997). • incorporate business logic of greater scale and scope. • (for these reasons) be more difficult to maintain (Banker et al. 1993). • (for these reasons) require more frequent maintenance attention (Kemerer and Slaughter 1997). • require more resources to replace. Cross-associations: • Larger systems tend to be associated with greater portfolio complexity, as they also tend to be central to the portfolio.
Portfolio Complexity	Systems with greater portfolio complexity tend to: • require more cross-functional coordination in maintenance. • be maintained in closer coordination with other systems. • (for these reasons) require more frequent maintenance attention. • be more problematic to replace. Cross-associations: • Systems with greater portfolio complexity tend to be larger, in order to accommodate this complexity.

With regard to system size and its effects, again, in the case of the maintenance effort, we merely reassert what has been found from earlier research (e.g., Lientz and Swanson 1980). Larger systems require more maintenance because of their sheer scale, typically measured in lines of code (LOC), and/or in some instances "function points" (Albrecht and Gaffney 1983; Banker et al. 1993; Kemerer 1993). Larger systems are also likely to be more structurally complex, which complicates further the maintenance task, further requiring greater effort (Kemerer 1995).[6]

The likely effect of system size on remaining life expectancy is more difficult to assess, suggesting competing hypotheses. Smaller systems might tend to have greater expected remaining life in that their scale would not be so individually demanding of maintenance resources. Their lesser complexity should also facilitate the maintenance effort (making continued maintenance more economical and the system less likely to be targeted for replacement). They should be more easily adapted where incremental change is necessary and hence more likely to be kept up-to-date with respect to user needs. Smaller might conceivably be better with regard to maintainability and expected remaining life. In which case:

(H2) Where the system's size is greater, (1) the maintenance effort is greater and (2) remaining life expectancy is shorter.

Larger systems, however, might tend to displace smaller systems in organizations, because maintenance resources are specialized toward larger systems where they are most needed. Smaller systems might tend toward isolation in the organization, where they would "starve" to death or fall prey to larger—"bigger and better"—replacement systems. Perhaps most significantly, larger systems might also be advantaged because it is more difficult to marshal the resources needed to replace them. The threshold for their replacement may in effect be set higher, leading to their relative longevity. Therefore, a good case can be made for a rival hypothesis:

(H2') Where the system's size is greater, (2') remaining life expectancy is greater.

Next, we consider the likely effects of portfolio complexity as discussed above. In the case of the maintenance effort, we argue first that, to the extent the system supports cross-functional business coordination, maintenance is likely to be greater, in that coordinative demands and adjustments between business functions are likely to be reflected in demands for changes to the software. Moreover, changes to the software may need to be negotiated across functions. Second, to the extent the system is closely related to other systems in the systems family (through the data that are passed from one system to another), maintenance is likely to be greater, in that changes to these other systems are likely to have ramifications. There will be a need to coordinate maintenance across systems, requiring greater effort.

Again, the likely effects on remaining life expectancy are more difficult to ascertain, suggesting competing hypotheses. Expected remaining life might be greater where the system's portfolio complexity is less, facilitating the ongoing maintenance effort. Where business functional and familial complexities are greater, and maintenance requires more effort, this may motivate the search for a new system with an architecture better suited to meet this complexity. In addition, the application assumptions of systems with high portfolio complexity may erode more quickly than the assumptions of simpler systems. Because they are thus exposed on a broad front, these more complex systems are not as likely to escape organizational change initiatives. Their useful lives may be shorter on the whole. Portfolio simplicity, rather than complexity, may conceivably be better with regard to maintainability and expected remaining life. In which case:

[6]System size in lines of code (LOC) is a well-known indicator of software complexity (Kemerer 1995). While software complexity is arguably more a matter of modularization and branching density, than it is a matter of sheer scale of code (Banker et al. 1989 1993), LOC has nevertheless been its most frequently used measure. Studies also show that LOC is typically highly correlated with other complexity measures of internal structure (Kafura and Reddy 1987). In the present research, we will use only the LOC measure. Strictly speaking, we measure software size, not complexity.

(H3) Where the system's portfolio complexity is greater, (1) the maintenance effort is greater and (2) remaining life expectancy is shorter.

Again, however, a good counter-argument for the rival hypothesis can be made. A system's portfolio complexity may tend to bind it to the larger organization, making it more problematic to extricate and replace, even where desired. Alternative systems solutions may also be more difficult to devise and implement. Off-the-shelf alternatives may not be available. The expected life of such complex systems may tend to be greater, not shorter, contrary to the prior reasoning. In short:

(H3') Where the system's portfolio complexity is greater, (2') remaining life expectancy is greater.

Finally, we consider the ramifications of the equilibration hypothesis as discussed above. We suggest that there are basic offsetting effects in equilibration, the net effect of which is uncertain, allowing for competing hypotheses.[7] Where the maintenance effort is greater, it may signal approaching end of system life to managers. Estimated remaining life may be short, where the effort is noticeably greater and the opportunity costs associated with continued system maintenance are viewed as high.

However, remaining life expectancy may also be short because replacement opportunities are compelling even apart from the current maintenance effort. In particular, a replacement package bought off the shelf may promise better functionality and usability in addition to reduced maintenance costs. In such a circumstance, when system replacement is foreseen (even planned), management may move to reduce or at least limit the current system maintenance effort. In particular, discretionary maintenance in the form of user enhancements may be foregone as much as possible. In effect, the reduced estimated remaining life may signal a moderation of the maintenance effort.

Thus, greater remaining life may alternatively be associated with more maintenance effort, on balance, rather than less. In sum, because of the hypothesized offsetting effects, whether there is a predictive net effect in either direction between the two related variables is uncertain, subject to empirical research. Either:

(H4) Where the maintenance effort is greater, remaining life expectancy is shorter and vice versa.

Or:

(H4') Where remaining life expectancy is greater, the maintenance effort is greater and vice versa.

In summary, our rudimentary theory allows for several different interpretations of how a system's age, size, and portfolio complexity should influence its maintenance and expectations of its remaining useful life. It is necessary to sort out the likely validities of these competing claims. Accordingly, we next subject our reasoning and hypotheses to exploratory analysis of data that can in turn inform them.

Method and Data

We examine the research hypotheses with selected data from an information systems census completed in the winter of 1994. The purpose of this census was to learn about the life cycles of the current installed base of business application software—its origins, functionality, complexity, aging and growth, care and maintenance, and

[7]As suggested earlier, our equilibration hypothesis is not really testable in the present research model and correlational study. Should a net effect be found to be "zero," the result (however unlikely) would still be consistent with the model. Of course, a significant net effect in either direction, while perhaps more likely given the hypothesis, might nevertheless be argued to be spurious and due to some other causal arrangement, reflecting a deficiency in the exploratory model. With a more sophisticated research model, we might, through causal analysis, attempt to assess the specific component effects. However, this is beyond the scope of the present study.

plans for system replacement and innovation.[8] A diverse group of 54 North American organizations responded to a written invitation to participate, describing a total of 758 systems among their application portfolios.[9] As these firms are not necessarily representative of a well-defined larger organizational population, the resulting data should be understood to come from a convenience sample, notwithstanding its diversity.

The data for the present research, in which the unit of analysis is the individual system, comprise 11 variables as described in Table 2. They include four contextual control variables and seven research variables pertinent to our model. The control variables include organizational size, as indicated by the total number of organizational employees, which controls for organizational differences that may impact upon system maintenance, a significant issue inasmuch as we will pool system level data across different firms. They also include three variables pertaining to operational and development technology, which may differ both across and within organizations.

Specifically, each system is described according to whether its processing platform is a mainframe or not, the relative amount of its code originally purchased rather than developed in-house, and whether its principal programming language (in which 50% or more of the system code is written) is COBOL or not. We note that applications systems developed in-house and written in COBOL for a mainframe characterize the classic situation popularly associated with the maintenance of so-called "legacy systems."[10]

Among the seven research variables, two are used as independent variables, three as indicators for an independent but latent variable, and two as dependent variables, all modeled together as specified in the next section. The independent variables include classic measures of system size in thousand LOC and system age in years since original installation. The three indicators of the latent variable, portfolio complexity, include business functional complexity as measured by the number of cross-functional business links supported by the system,[11] plus two indicators of familial complexity, the number of other basis systems upon which the system relies for its data and the number of other dependent systems which rely for their data on the system.[12]

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[8] Swanson (1989) first offered the proposal and general motivation for an information systems census. Broadly, the argument is that we may usefully study populations of systems within and across organizations in a manner much like we study human populations in terms of their demographics. In particular, systems tend to originate and grow within families (also often termed "portfolios") and their life cycles need to be studied and understood in this context. "Household surveys" of systems are useful, just as household surveys of humans are useful.

[9] While the survey employed a relatively short-form questionnaire instrument (available from the first author), the task of completing it was daunting inasmuch as it required that an entire application portfolio be enumerated and factually described through data gathered on individual systems. We did not expect that more than a small fraction of those we contacted—some 934 North American firms and their CIOs from a personally developed mailing list—would be able to participate. In the aggregate, we obtained data on a substantial and diverse collection of systems across a good variety of firms. The number of systems described averaged 14.4 and ranged from two to 53 among respondents. Among the organizations, almost half are located in California, while the rest are widely spread throughout the U.S., with one in Canada. Among industries, manufacturing accounts for more than one third of the respondents, while the financial and services sectors are also well represented. We speak further to the diversity and representativeness of the sample when we consider our actual data below.

[10] We note further that including the programming language variable as a contextual control, even with its present primitive metric, may be important because we measure system size in LOC, which is likely to differ across source languages.

[11] The business functions are purchasing and supply, operations, distribution, marketing and sales, customer service, accounting and finance, personnel, administration, and engineering. Where but one function is supported, functional complexity = 0; where two functions are supported, functional complexity = 1; where three functions are supported, functional complexity = 3; where four functions are supported, functional complexity = 6; and so on. In general, functional complexity = $n(n-1)/2$, where n = number of functions supported.

[12] Because these two familial associations are different in kind, we use two measures here rather than one. We have observed from pilot studies that systems within a portfolio will likely differ significantly on these two measures. A few core systems may provide data for the others that are built around them, for instance. Their high scores on the number of dependent systems measure may distinguish these core systems.

Table 2. Variables and Metrics

Contextual Variables	
Organizational Size	
Organizational employees	FTE
Operational and Development Technology	
Platform type	Mainframe = 1, Other = 0
Purchased code amount	Percent of system total
Principal programming language	COBOL = 1, Other = 0
Research Variables	
Independent	
System size	Thousands of LOC
System age	Years since installation
Business functional complexity	Cross-functional business links
Basis systems	Basis systems, number
Dependent systems	Dependent systems, number
Dependent	
Maintenance effort	FTE assigned
Remaining life expectancy	Estimated years

The two dependent variables include the maintenance effort as indicated by the number of maintenance staff (in FTE to one decimal place) assigned to the system and the remaining life expectancy of the system in years. These measures are thus simple and straightforward ones. However, we caution that in the case of remaining life expectancy, the census data afforded us with organizational estimates that may mask substantial complexity in the individual judgment(s) underlying them.[13] We revisit this issue below. In the case of the maintenance effort, we also point out that very different types of maintenance work, including enhancements, are subsumed under our metric.

Analysis and Findings

Simple descriptive statistics for the 11 variables constituting our data are shown in Table 3. The number of cases reported for each variable differs according to the questionnaire items left blank by respondents. The total number of cases with complete data was 366, largely because many systems were not documented as to their size. Several variables, specifically those representing organizational size, system size, and maintenance effort, presented naturally skewed distributions calling for logarithmic transformations prior to subsequent correlational and other parametric analysis.[14]

[13]For purposes of the census, managers responded on behalf of their organizations. We sought no individual judgments as such. Nevertheless, where the organizations did not routinely estimate remaining life expectancies, such judgments were no doubt involved in answering the question.

[14]In the case of the maintenance effort, where the respondents indicated zero maintenance, these data were treated as anomalous and excluded from further analysis as presented here (zero is undefined in logarithmic transformation). Zero maintenance was judged to present a structurally different case, where it

From Table 2, we can also characterize our pooled sample of systems. Somewhat more than half operate on a mainframe (61%) and/or are written in COBOL (55%). About a third of their code (32%) was originally purchased, on average. Systems further average slightly under seven years of age, with about five years of expected life remaining, suggesting a 12 year average likely lifespan overall.[15] They are also large, averaging almost 650,000 LOC, and are maintained by three-and-a-quarter FTE. As might be expected, there are ample variances associated with these simple averages.

Thus, our sample includes a greater proportion of large systems when compared to prior studies such as Lientz and Swanson (1980), where systems averaged only about 50,000 LOC and were maintained by less than one-and-a-half FTE, or Nosek and Palvia (1990), where systems averaged 200,000 LOC and were maintained by seven-and-three-quarter FTE. Clearly, our sample data are biased toward large systems being maintained by large shops, consistent with the CIO representation in our mailing list. This bias is further underscored when we consider only the complete cases for which we have data on system size. These systems tend even more to be classical custom-built legacy systems maintained by larger shops.[16]

Pearson correlations among the variables (for the complete cases) are shown in Table 4; about half of these are significant at the .05 level, suggesting a rich pattern of modest associations. Only three correlations exceed .40. Dependent and basis systems are correlated at .48, which is somewhat high but consistent with retaining them as distinct measures of two different aspects of familial complexity. Maintenance effort is correlated at .66 with system size, as might be expected. The use of COBOL correlates at .45 with a mainframe platform for development and operations.

To test our research model, we specified a structural equation model (SEM) with latent variables. The SEM approach seems particularly appropriate as we are testing a priori theoretical assumptions against empirical data and further exploring the existence of a new construct, namely portfolio complexity, defined as latent, using three variables as indicators. As Chin (1998) points out, SEM provides substantial flexibility to model relationships among multiple predictor and criterion variables and to construct unobservable latent variables. In addition, the pattern of multiple associations (and, therefore, potential multicollinearity issues) found in our data argues for such a holistic approach over methods such as simple general regression, which assume independence of explanatory variables. Finally, the fact that one of our hypotheses is formulated as an equilibration provides another reason for using SEM, since this type of hypothesis is more easily examined in the context of a multivariate framework.

Data were analyzed using EQS for Windows 5.7 (Bentler and Wu 1995), a package specifically developed to provide tools for SEM in the context of the Bentler-Weeks model (Bentler and Weeks 1980). We chose EQS over LISREL because several of our variables notwithstanding transformations presented skewed distributions likely to violate the assumption of multivariate normality. In such cases, EQS allows for the calculation of a scaled χ^2 statistic (Satorra and Bentler 1988) reported to be highly reliable for estimation purposes (Hu et al. 1992).

Adapting from our theory presented earlier, the model we tested appears in Figure 2. It incorporates two independent variables, system age and system size, and one independent but latent variable, portfolio complexity, with three indicators: business functional complexity, the number of other basis systems upon which the system relies for its data, and the number of other dependent systems which rely for their data on the system.

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is not reported because it has been outsourced, for instance. Still, this interpretation is arguable. An alternative interpretation would be that zero maintenance was "negligible" to the one FTE decimal place allowed for on our form. As a supplementary exercise, we recoded zero as 0.01 and redid our analyses, coming largely to the same findings and conclusions.

[15]We note with interest that the 12 year average likely lifespan corresponds precisely with the average age of systems under replacement in a dozen portfolios described in previous research by Swanson and Beath (1989, p. 440).

[16]Note further that our respondent sample is no doubt biased toward firms with good data on their portfolios, when compared to non-respondents, a point to which we will return later.

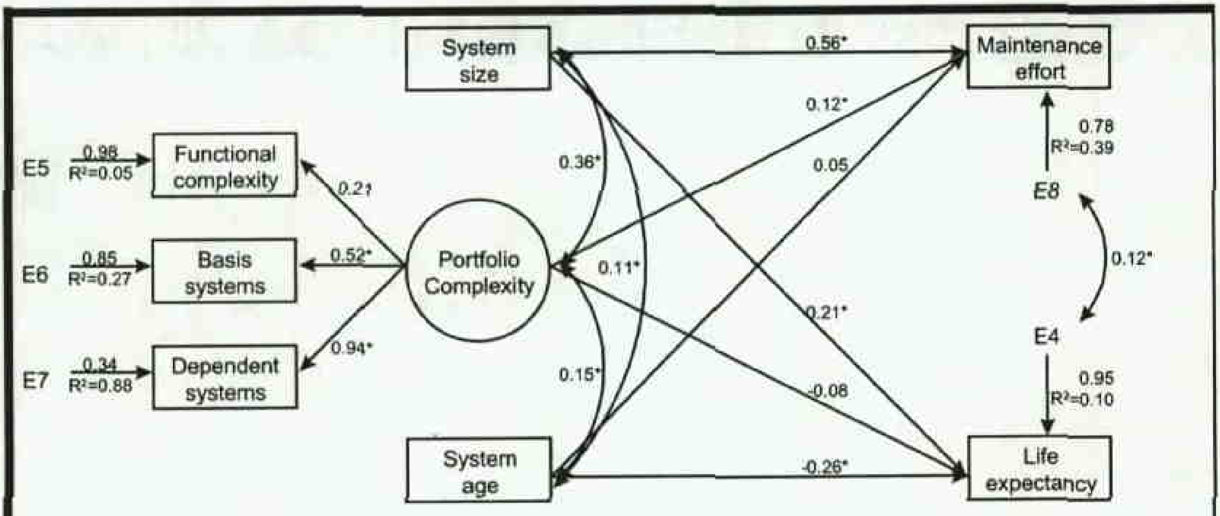
Table 3. Simple Descriptive Statistics					
Variable	**N**	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Organizational size	718	12,632.00	16,354.00	100	75,000
System age	712	7.22	5.70	0	29
Platform type	758	0.61	0.48	0	1
System size	417	645.63	996.65	2	6,750
Purchased code amount	683	31.58	42.11	0	100
Programming language	758	0.55	0.50	0	1
Maintenance effort	689	3.28	8.24	0	100
Life expectancy	697	4.92	3.21	0	20
Functional complexity	758	2.75	5.40	0	36
Basis systems	758	2.41	3.00	0	15
Dependent systems	758	2.41	3.03	0	5

Note: Organizational size, system size and maintenance effort are given logarithmic transformations for all subsequent analyses.

Each of these three independent variables is hypothesized to have a direct influence on each of the two dependent variables: maintenance effort and remaining life expectancy. The correlations among the independent variables are left free to be estimated. The correlation between the residuals of the two dependent variables is also assumed free, in order to incorporate possible additional correlation not operationalized through the independent variables. Note that it is here that our tested model differs on the surface from our research model, which posits a bi-directional equilibration effect between the dependent variables. Because we cannot directly test for such an effect with our data, we look instead for a significant correlation between the residuals of the dependent variables assumed not directly related. Should we find it, it may be interpreted as evidence consistent with the posited effect.

We estimated the model via EQS using conventional maximum likelihood estimation. Results confirmed that notwithstanding several transformations, some of our variables were non-normally distributed (Mardia's coefficient exceeded three). As suggested by Mardia (1970), this led us as a precaution to obtain a robust set of model estimates, summarized in Figure 2.

The overall model appears from the estimates to provide a good explanation of the data. The value of its χ^2 was 9.17 with eight degrees of freedom, yielding a p-value of 0.33 (7.98 and 0.44 for the Satorra-Bentler scaled χ^2 in robust estimation.) For the independence model, the value of the χ^2 was 398.71 with 21 degrees of freedom ($p < 0.0001$). Hence, we cannot reject the hypothesis that the proposed model adequately explains the relationships among our data. Indeed, the iterative process converged without special problems in 11 iterations, and all the fit indices are seen to suggest an excellent fit. In particular, the value for the Root Mean Square Error of Approximation (RMSEA) was 0.02, well below the critical value of 0.05 proposed by Browne and Cudeck (1993) as a good indicator for a close fit.



Independence Chi-square	= 398.18
Degrees of freedom	= 21
Model Chi-square	= 9.17
Degrees of freedom	= 8
P value	= 0.328
Satorra-Bentler Chi-square	= 7.98
P value	= 0.435
Bentler-Bonnett normed fit index	= 0.977
Bentler-Bonnett nonnormed fit index	= 0.992
Comparative fit index (CFI)	= 0.997
Robust Comparative Fit Index	= 1.000
RMSEA	= 0.02
Lower bound for RMSEA CI	= 0.00
Upper bound for RMSEA CI	= 0.06
LISREL GFI	= 0.993
Number of iterations	= 11

Figure 2. Model Diagram and Results of the Estimation

Several alternative models were also explored, but all of them performed poorly in relation to the initial model, with one exception: when business functional complexity is dropped from the latent variable, fit indices improve and the p-value rises to 0.64. However, because the values of the parameters in the model do not change substantially and the p-value of the initial model is good enough to warrant interpretation, we decided to retain the indicator in the model, thus eschewing opportunistic ex-post revision and preserving the original meaning of the factor.

We note too that the portfolio complexity construct with the three indicators yielded a Cronbach's alpha of 0.6, large enough to consider it adequately measured according to the guidelines suggested by Nunnally (1978). The value of Cronbach's alpha for the construct without business functional complexity was obviously higher, 0.8, but a confirmatory factor analysis showed that the three variables were systematically grouped together in a single factor with significant loadings.[17]

[17]We used the criteria provided by Hair et al. (1995) to determine the importance and significance of the factor *loading of each item: loadings greater than 0.30 are* significant, those greater than 0.40 are more important, and those greater than 0.50 are very significant.

Table 4. Pearson Correlation Coefficients

	System age	Basis systems	System size	Functional complexity	Dependent systems	Programming language	Life expectancy	Maintenance effort	Organizational size	Platform type	Purchased code amount
System age	1.000										
Basis systems	.036	1.000									
System size	.075	**.206**	1.000								
Functional complexity	.009	**.139**	**.234**	1.000							
Dependent systems	**.131**	**.482**	**.303**	**.156**	1.000						
Programming language	**.352**	.084	**.216**	**-.120**	**.129**	1.000					
Life expectancy	**-.226**	.049	**.180**	.101	-.049	**-.151**	1.000				
Maintenance effort	**.133**	**.157**	**.656**	**.209**	**.288**	**.125**	.060	1.000			
Organizational size	-.024	-.082	**-.112**	**-.179**	-.094	.091	**.121**	**-.165**	1.000		
Platform type	**.269**	-.018	.088	-.078	.022	**.450**	-.009	**.118**	**.163**	1.000	
Purchased code amount	**-.131**	.011	.059	.081	-.080	-.070	.025	-.068	.018	**-.177**	1.000

In **bold** = Significant at .05 level
N = 366

Standardized estimates of the model's path coefficients also appear in Figure 2. Interestingly, correlations among the independent variables are all positive and significant, underscoring the usefulness of the SEM approach. Between the independent and dependent variables, two paths are found not significant: from portfolio complexity to life expectancy and from system age to maintenance effort. The remaining four paths are all significant, the strongest two being the positive association between system size and maintenance effort (0.56) and the negative association between system age and life expectancy (0.26). Path coefficients for system size and life expectancy (0.21) and for portfolio complexity and maintenance effort (0.12) are also significant. Finally, the residuals of the two dependent variables, life expectancy and maintenance effort, show a positive and significant correlation (0.12), consistent with the equilibration hypothesis. The R^2 for maintenance effort (0.39) is seen to be notably better than that for life expectancy (0.10).

In order to explore the contextual stability of the model, we next examined four elaborated models, each of which incorporates one of our control variables as an added independent variable. In each case, paths were drawn from the control variable to each of the dependent variables. The correlations among the control variable and the remaining independent variables were left free to be estimated. None of the four elaborated models showed substantial differences in the values of the original parameters, although fit indices were better in two cases (platform type and purchased code amount) and worse in the remaining two (organizational size and programming language). In three cases, none of the paths from the control variable to the dependent variables were significant. In one case, programming language, we found significant paths for both life expectancy (-0.18) and maintenance effort (-0.11). The correlation between the residuals of these two variables was 0.10, lower than the one in the original model, indicating that the introduction of this control variable helped to explain a slightly larger amount of variance.[18] Another difference found was the path between system age and maintenance effort, which turned from insignificant to significant (0.08). Such an outcome is somewhat common in this form of analysis, because with decomposition of effects, the presence of an added relationship, even an insignificant one, may mask other existing relationships. On the whole, then, we found our model stable under the introduction of the four different contextual controls.

Continuing the analysis, the model was cross-validated following MacCallum et al. (1994). The sample with complete cases was randomly split into two subsamples, using one as the calibration set and applying the resulting estimates to the second subsample as a validation set. This procedure was repeated 10 times, generating 20 subsamples. An a priori Wald test was performed in each second subsample using as input the set of parameters estimated in each first subsample. For all cases, correlations between these a priori constants and the final estimates were higher than 0.9, further indicating stability of the model.

The statistical power of our model was not straightforward to test, in particular because our data contain a large number of missing values with a predominant pattern: many systems were not documented as to their size. Therefore, we followed Allison's (1987) and Muthén et al.'s (1987) approach to testing for statistical power in models with missing data: we created groups or subsamples of systems according to their pattern of missing data and we ran the model as a multi-sample analysis. Following the tables developed by MacCallum et al. (1996), statistical power for this multi-sample model was found to be 0.8, substantial enough to ensure our ability to detect and reject a poor model. Finally, to test this presumed ability, we explored several alternative models altering one or some of the relationships in the original model: all of them performed worse than our original model and most of them did not converge or else achieved probability values smaller than 0.001.

Discussion

In summary, our findings substantially support our research model. They provide evidence consistent with our equilibration hypothesis relating a system's remaining life expectancy to the maintenance effort. They establish the existence of a portfolio effect in accounting for the maintenance effort, although not remaining life expectancy. They indicate that larger systems are associated with a greater life expectancy, not only a greater maintenance effort. They confirm that older systems have a shorter remaining life expectancy, as should be expected, but not that older systems are directly associated with a greater maintenance effort.

Recall that in our equilibration hypothesis, we posited interacting and potentially off-setting effects. While a greater maintenance effort might signal lower life expectancy, the latter provides a reason for reducing the maintenance effort. Finding the residuals of these two dependent variables to be positively correlated; it appears that the latter effect may dominate the former one. Our interpretation is that managers likely moderate their maintenance effort where remaining life

[18] We should mention that the path between portfolio complexity and life expectancy was dropped from this particular model in order to avoid linear dependencies among parameters. We used a battery of Wald tests to assess which paths were the preferred ones to drop without affecting the overall fit of the model. The eliminated path was not significant in the original model.

expectancy is relatively short and sustain their maintenance effort where life expectancy is relatively long. Still, an alternative interpretation consistent with our findings might be that remaining life expectancy is rationalized in part by the maintenance effort.

Although we have not provided a strict test of the equilibration hypothesis, our correlational evidence is nevertheless supportive of it. Within our model, there is no other explanation for the positive correlation in the residuals of the dependent variables. Of course, we should caution that our model might be deficient and another variable(s) not included in our research might account for the present finding.

In the case of our hypothesized portfolio effect, our findings confirm that greater portfolio complexity is associated with a greater maintenance effort as conjectured. This complexity apparently stems more from familial complexity in terms of basis and dependent systems than it does from *business functional complexity, which does not* prove to be a significant indicator in our model. The suggested interpretation is that the greater the interdependencies of systems within the family, the greater will likely be the maintenance effort. Moreover, noting that portfolio complexity and system size are positively correlated in our data, this effect occurs beyond the additional code written to provide for such interdependencies. Nevertheless, we should caution that our present findings and analysis are at the system level only, and that further studies at the portfolio level with appropriate measures of internal interdependencies and integration are needed to confirm our interpretation. In addition, we did not find a significant portfolio effect for remaining life expectancy, contrary to our hypothesis. This further suggests caution in interpretation pending further research.

We found it especially interesting that larger systems were associated with greater life expectancy, in addition to greater maintenance effort. The apparent explanation here is that larger systems may in general be longer-lived. Where the investment is substantial, management may perhaps expect a longer useful life over which to amortize costs. We note that the research of Gode et al. (1990) and Chan et al. (1994) suggests that this may not be wise, given the rising maintenance costs associated with older systems. Still, management may find it easier to tolerate incremental increases in maintenance costs than to justify a major new development effort associated with replacement. Larger systems may face a significant threshold barrier in proposed redevelopment.

Larger systems might also be longer-lived for a very different reason. Specifically, because they incorporate more information processing rules, they might tend to be more important to the organization, which has required them and depends upon them. More than smaller systems, they might tend to have substantial political support. Kling and Iacono (1984, p. 1225) remind us that systems "live and develop through the energies of their promoters rather than 'evolve' through a 'life of their own'." Thus larger systems might be more likely to become institutionalized and sheltered from competing logics of retirement *and replacement. Still other explanations may also* be offered for the apparent relationship between system size and longevity, suggesting that further research is much needed on this issue.

Finally, it is of interest to confirm that older systems are indeed associated with shorter life expectancy, as should be expected. Eventually, age exposes all systems to prospective retirement and replacement for reasons already discussed. Somewhat surprisingly, however, older systems were not significantly associated with greater maintenance effort, although this insignificance is apparently at the margin and the sign is in the expected direction. We note that where the model was elaborated to include programming language as a control, the correlation increases slightly and the path becomes significant as expected.

Conclusion

The present exploratory study offers new evidence and insight into the life cycles of systems in organizations. It identifies maintenance as paralleling the usage phase of a system's life (Larsen 1998). It links in a novel way the effort to maintain systems in organizations with judgments made about their remaining life expectancy. It posits first of all that managers should be expected to equilibrate their allocation of effort in maintaining a system with their estimate of the system's remaining life. It further suggests a portfolio effect in system maintenance and expectations of remaining life. Exploratory findings confirm that a system's age, size, and portfolio complexity play significant explanatory roles in accounting for the maintenance effort and remaining life expectancy and that the latter are themselves further positively related. They also suggest that larger systems may tend to be longer-lived than smaller systems.

The emergent overall picture provides a twist on our initial comprehension of maintenance. We began our theorizing above by saying that the effort to maintain systems in organizations may be understood as aimed at extending their useful lives. While this statement remains true enough, our present evidence suggests that we should emphasize instead that useful lives give cause to extend the effort in maintenance. Our research explains more of the maintenance effort through life expectancy than it does life expectancy through the maintenance effort. It suggests that the maintenance effort is apparently scaled in part to a system's remaining life expectancy. Moreover, the size of systems apparently reflects management's investment in and commitment to their systems' useful lives. Larger systems are perhaps not so much the "burden" of maintenance as they are assets expected to provide corresponding returns to maintenance over a longer time period.

Managers planning the ongoing maintenance and redevelopment of their systems families may take all of the present findings into account. Such planning may be usefully informed by the collection of good local data on familial relationships among systems within the enterprise. This data should be structured so as to fit naturally within a repository supporting system development and maintenance across the firm. An interesting finding in the present research was that several of our non-respondents wrote thoughtful personal letters telling us that they would have liked to participate, but that the present state of their portfolios was such that they did not have good or ready enough access to the needed data. In the future, we would hope that better documented portfolios might make gathering data for a study such as ours easier for sympathetic would-be-participants to undertake.

At the same time, for practitioners, better documented and monitored portfolios should be helpful, even in some cases crucial, to more effective management of their systems' life cycles. As we suggested earlier, system retirement and replacement is now a common phenomenon in the firm. Moreover, the lives of systems do not simply take their own inevitable course; they are extended or shortened through management decision with important consequences. Consider, for instance, what can only be termed the example of the millennium. Faced with the pervasive Y2K bug throughout their portfolios, many managers have recently had to decide whether to invest huge sums in fixing current systems or instead to acquire, also at great expense, an integrated Y2K-compliant ERP package to replace core systems (Stedman 1998). In the absence of good, reliable data on their own portfolios, managers worldwide have had considerable difficulty even beginning to address this critical issue.

In addition to monitoring their portfolios in terms of basic demographic characteristics, managers may also wish to conduct regular, periodic performance or "health" assessments of individual systems. Such assessments can provide qualitative rationale in support of continued maintenance or replacement. From our own informal surveys of managers over recent years, we estimate that a significant fraction, some one third or more, of organizations do not yet conduct such assessments. We suggest that performance assessments can be an important tool in managing systems' life cycles.

With regard to the research reported here, we should caution that our present exploratory findings are much in need of further study, validation, and extension. The data for this study come from a diverse, but limited, sample of organizations, one not necessarily representative of any specific larger population to which one might wish to generalize. Our findings are necessarily suggestive, more than conclusive. Even apart from concerns about their external validity, the amounts of important variances explained in our sample data analyses are modest. Much additional light remains to be shed on the subject and the associated phenomena must be probed more closely.

Future research should examine how managers arrive at their judgments as to system life expectancies. The present research was limited by its data to the organizational product of this judgment and not its particulars. It should be especially interesting in future studies to probe aspects of uncertainty associated with judgments of life expectancies. In this regard, we note that the field of technological forecasting (Helmer 1967) has developed adaptable methods for reaching a consensus about such uncertainties. Additionally, it is important to explore the biases likely to attend these judgments. We note for comparison the long and notorious history of overly optimistic forecasts of when systems projects should be completed.

Further exploration and validation of the equilibration hypothesis offered here is also needed in future research. The present cross-sectional study was only motivated by this hypothesis; it was not designed to confirm it. Future studies should examine managers' decision processes in their specifics to properly assess the validity of the hypothesis. Such studies might also probe the reasonableness of these decision processes, taking more of a normative view of them. Ultimately, we might aim to provide managers with better guidance in their efforts to allocate appropriate resources to maintenance while at the same time taking appropriate account of a system's expected remaining life.

Finally, extensions to the present research should also probe the relationship of our findings to actual retirement and replacement decisions. Here we have studied managers' expectations only. Future studies might usefully take a micro-analytic longitudinal approach focused on the eventual convergence to the decisions themselves. How do managers ultimately make the retirement and replacement decision? Do they tend to focus on the maintainability of the present installed system? Or do they tend to be driven by externally-driven opportunities seen elsewhere, for example, in a business process reengineering initiative or in a commercial package said to incorporate the "best practices" of the industry? Are managers somehow able to strike some "right balance" in their approach to the retirement and replacement issue and, if so, how do they go about it? These interesting and important questions remain unanswered.

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