A MODEL ACCOUNTING PLAN FOR SPECIAL EDUCATION

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Current systems for monitoring the enrollments and status of special education programs do not meet current demands for increased accountability. Project MAP (Model Accounting Plan) attempts to meet this demand. MAP is a demographic accounting model for monitoring the transitions of special education students as they progress through the school system and for the year after they graduate. The MAP was pilot tested with 1,100 secondary level special education students in one Northern California school district. Using existing pupil count data and a follow-up one year later, the MAP describes and predicts the paths special education students follow, taking into account the student's age, handicap, and instructional setting assignment. The MAP provides previously unavailable data to special educators and decision makers at all levels regarding program effectiveness and resource allocation and poses useful questions for further study.

As special education programs have increased in number and in size, the burdens of documenting and ensuring program effectiveness have grown. Federal and state demands for greater accountability have led to various program monitoring requirements that have failed to provide meaningful information for educators, administrators, and decision makers at all levels. The critical link between monitoring and improving special education programs has not yet been forged.

Status and Problems Involved in Current Monitoring Systems

Current systems for monitoring the enrollments and status of special education programs require the collection and reporting of information at every administrative level. Central to this monitoring is the annual count of special education students, required by the U.S. Office of Special Education Programs (OSEP) and used as a basis for resource planning. Conducted in April and December of each year, the pupil count is intended to inform administrators about the enrollments of special education students by type of program, handicap, age, and ethnicity. Schools assemble and submit these data to district offices, which in turn aggregate or send these data directly to an intermediate educational agency such as a county office. Intermediate agencies aggregate and send these data to state education agencies that report them to federal officials.

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In concept, this system requires a routine data collection effort to yield potentially useful information.

In fact, however, this system is severely inadequate in providing information that can be critically useful to special educators, consumers of special education, and educational decision makers at every level. Currently, the annual pupil count is a simple census that provides a snapshot of special education enrollments at a single point in time. It provides counts of only those students currently enrolled in special education and does not relate information on enrollments from one year to the next. At best, the current system describes the numbers and types of students receiving certain types of special education services, and can shed some light on questions of resource allocation.

However, because the system does not track students from one period to the next and does not follow up students who have graduated or left the school system, it fails to address the issue of *transition* that is of such vital concern to special education today: What, in fact, happens to special students when they face the "real" world? How effective are special education programs in preparing students for this critical transition? In addition, the data are often highly inaccurate, characterized by inflated counts, undercounts, clerical errors, and sometimes deliberate distortions to justify allocation requests. Efforts are under way in several states to improve the accuracy of these data by centralizing data collection at the state level; whether these efforts have promise remains to be seen. In any case, in its current condition, the pupil count is seen by many school districts as a burdensome and largely meaningless exercise.

Proposed Solution: A Model Accounting Plan (MAP)

In response to increasing demands for accountability and recognition that existing data were inadequate, the Office of Special Education Programs granted 3-year support to the American Institute for Research for Project MAP (Model Accounting Plan). Project MAP is a demographic system for monitoring the transitions of special education students while they progress through the school system and for the year after they graduate or leave the system. It is a model, as well, for making predictions about the likely paths special education students will follow, and for assessing the effectiveness of programs in meeting their stated goals and objectives. Implemented at the local level, the MAP puts the burden on local educators to track each special education student and to provide meaningful data that can be used by special education personnel, consumers of special education (parents), and policy makers at all levels.

This article focuses on the MAP and its significance to special education. First, we will briefly discuss the design, methodology, and analyses involved in the MAP pilot test, including the technical details in an appendix. We will then describe the results and discuss in detail the potential benefits of the MAP to special education, the limitations of the model, and suggestions for further study.

METHOD

An Overview of Demographic Accounting

The MAP employs a demographic accounting procedure to examine issues related to attainment and attrition in special education. Since being proposed by Sir Richard Stone in 1971, demographic accounting has been used in a variety of contexts including studies of population dynamics and labor force participation. It has since been explored in relation to education by McMillen and Land (1979) and by Russ-Eft and her colleagues (1981). When applied to education, demographic accounting tracks population changes such as new enrollments or withdrawals through various educational settings or instructional programs. It can also estimate the likelihood of future changes, or transitions, and thereby describe patterns of these transitions and the ways in which these patterns change over time.

Demographic accounting requires that the status of an account be measured at two points in time, separated by a standard period such as a year. The whereabouts of all persons present at the start of the period must be known at the end of the period, and new arrivals must be identified for the accounting to succeed.

The individuals included in a demographic accounting framework may be divided into categories based on descriptive information such as employment status or instructional setting. In special education, for example, standard instructional assignments such as Special Day Class, Resource Specialist Program, or Designated Instructional Services might define these categories.

As mentioned above, accounting for the movements of students into, out of, and within special educational programs, and following graduation, allows transition probabilities to be estimated. Transition probabilities measure the likelihood with which individuals move among states of the system within the period specified. For example, given that students are enrolled in a Special Day Class, we might use transition probabilities to estimate the likelihood of their remaining in the Special Day Class, moving to a Resource Specialist Program or to a Designated Instructional Service, or being mainstreamed the following year. We assume, for the purposes of the model, that these transition probabilities are stable for the period of interest.

In a demographic accounting system for special education, we can in turn use transition probabilities to estimate the educational expectancies of special students. Educational expectancy measures are indicators of likely educational attainments for particular ages—for example, being mainstreamed by age 16 or being graduated and at work by age 21.

Ideally, demographic accounting procedures can empirically compute transition probabilities for pairs of years covering the entire time period of interest—for example, the 4 years of high school—and in turn determine educational expectancies for the same period. However, it it not always possible to obtain complete data on transitions. Demographic accounting provides methods for estimating these measures with less than complete data.

Sample. The principal aim of Project MAP in Year 1 was to relate the school experiences and achievements of special students to their performance in the worlds of continuing education, work, and independent living. Therefore, our Year 1 sample included all secondary students enrolled in special education programs (Grades 9 to 12 or nongraded), as well as all graduates from special education programs during the previous year. The age range was 12 to 21 because at 21 years of age most students must turn to agencies outside of school for necessary services. Including a 1-year follow-up of graduates provided for the most direct estimation of in-school influences on transitions following graduation. (Graduation, for the purpose of this study, meant that a student had been officially certified as having completed all necessary work by the school district. We made no attempt to distinguish graduates according to the various standards for graduation that might have been applied.)

One northern California high school district, operating 13 regular and special service schools, served as the MAP pilot/test site. This district enrolls approximately 1,100 special education students out of a total enrollment of almost 9,000 students. The student population, generally, comes from middle- to upper-middle-class families, with median family income in 1984 ranking 4th out of the 58 counties in the state at $22,390, and only 3% of the families qualifying for AFDC assistance. Ethnic minority group members comprise approximately 32% of the total student population, with the largest groups drawn from the Asian (15%) and Spanish-speaking (8%) communities.

Of the 1,099 special students whose records and follow-up data were analyzed, the majority were males (63%), white-Anglo (76%, with Hispanic students comprising the next largest group at 12%), and learning handicapped (77%, with the next largest group—Other Health Impaired students—comprising 7% of the total). These special students were about evenly distributed across Grades 9 to 12.

Time Period for Monitoring. As mentioned earlier, demographic accounting requires collecting data on student enrollment and postgraduation status at two points in time, separated by a standard period of some significance to educational program administration. We selected one calendar year, so that patterns of enrollment, transition, and attrition could be related to single years of age and to annual planning cycles. To ease the data collection burden on administrators, we chose to use existing data as much as possible. The annual pupil count would serve as our baseline data—that is, the data for the beginning of the year—on students participating in special education. We selected the December count in order to return the results of MAP analyses to participating jurisdictions by early spring. This timing would facilitate timely decision making related to allocating resources for pupil services. Because subsequent pupil counts are not related to previous counts, it was necessary to require an additional census the following December that would define the whereabouts of every pupil identified in the previous count. This additional census included the telephone follow-up of prior year graduates.

Instructional Settings. As suggested earlier, a variety of categories can be used in a demographic accounting system. For the Model Accounting Plan, we chose to use instructional setting assignments as the frame of reference for several reasons: (a) Such settings indicate the extent to which students require special services and reflect judgments regarding which environment is the least restrictive; (b) administrators plan their annual budgets in terms of these instructional settings; (c) instructional settings are likely to influence students' postgraduation attainments in terms of the preparation they provide for independent functioning; (d) these settings imply no "one way is the right way" direction to the schooling experience—special children may move among instructional setting assignments depending on their needs.

We selected the following three instructional settings for the MAP because they are an integral part of the existing pupil count procedures: (a) Special Day Class (SDC)—typically an all-day, contained classroom; (b) Resource Specialist Program (RSP)—one or two periods of specialized instruction in general academic areas such as history or mathematics; and (c) Designated Instructional Service (DIS)—very specialized service for one school period, such as specially designed physical education or speech therapy to students who otherwise function satisfactorily in the mainstream program.

Because the MAP must account for the status of *all* active special education students at the beginning and end of the time period, we defined two other instructional setting assignments in special education: Other Special Education Setting, to account for small enrollments in special schools and home instruction programs, and Unknown Special Education Setting, to account for enrolled special students whose assigned settings were missing from the database. Of the 1,099 cases included in MAP analyses, 20 were classified as enrolled in an Other setting and 12 were classsified as enrolled in the Unknown setting.

In addition, we needed a way to categorize those students who move out of special education for various reasons. We therefore defined four principle exits from special education: (a) Mainstream/other jurisdiction—all special students who either moved into the full-time mainstream program or transferred to a school outside of the jurisdiction; (b) dropout—special students who were officially classified as dropouts, plus those whose withdrawal codes indicated that the reason for their having withdrawn was unknown; (c) graduation *and* at postsecondary school or work; and (d) graduation *but* at neither school nor work. The last two categories included students who had been recently enrolled in special education and were officially coded as graduates by the management information system, plus those who had reached the age of 21 years and were no longer eligible for school-based services. We included these last two groups to gather data for the first year following graduation, a critical period of transition.

Unfortunately, the extent to which these exits from special education are documented by local jurisdictions is less than complete. In some cases, records for students who leave special education may actually be removed from management information systems, making it impossible to trace why they moved or where they have gone. In these situations, considerable effort may be needed to search records and refresh staff recollections to determine the status of students who have exited the system.

In summary, then, we used the following nine categories, covering both in-school instructional setting assignments and exits from the special education system, to define the MAP:

Enrollment in School
- Special Day Class (SDC)
- Resource Specialist Program (RSP)
- Designated Instructional Service (DIS)
- Other Special Education Setting
- Unknown Special Education Setting

Exit from Special Education
- Mainstream/Other LEA jurisdiction
- Dropped out of school
- Graduated, at school or work
- Graduated, neither at school nor work

Effects of Age, Handicap, Sex, and Ethnicity. It is important to consider whether transition probabilities for a population are subject to systematic influence by age, type of handicap, sex, or ethnicity. For example, were age a factor in determining transition rates, with older students more likely to be returned to the regular program, then projections of attainments based on these rates would have to take the age of students into account.

We conducted analyses (log-linear methods described in more detail in the Technical Appendix) to determine which of these factors alone or in combination were important variables to include in the model. We found age to be the single statistically significant factor. Because of the limited sample size, we defined four age groups based upon observed transition patterns: 12 to 15 years, 16 years, 17 years, and 18 to 22 years.

Although we did not find handicapping condition, sex, or ethnicity to be statistically significant factors in determining transition, we decided to include handicap in our Year 1 analyses because of the strong conceptual relationship between type of handicap and transition. In addition, observed frequencies suggested different patterns of transition for students with different handicaps. We used these observed frequencies, as well as the similarity in service requirements associated with the various handicaps, to define these three major handicap groups and subgroups: orthopedic disability (orthopedically handicapped, other health impaired), learning disability (specific learning disability, severe language handicap, hard of hearing), and retardation or severe sensory disability (educationally mentally retarded, trainable mentally retarded, developmentally disabled, visually handicapped, deaf-blind, deaf, speech impaired, seriously emotionally disturbed, autistic).

It is important to note that these handicap clusters seemed appropriate for grouping handicaps for our pilot test, according to the transitional patterns observed in the data. They are not, however, the only way to group data. The MAP model, in fact, allows selection and grouping of categories in any meaningful way.

Analyses of the MAP Data

Structure of the MAP. We counted special education students at two points in time, according to the nine instructional settings in which they are placed. To visualize these settings as part of the MAP, we defined a square, 9 x 9 matrix shown in Figure 1. The matrix includes 81 cells, each denoting the number of special education students who moved from one of the nine settings at the beginning of the period to another one of the nine settings at the end of the period. (We used a square, 9 x 9 matrix because all computations of educational expectancies based on transition probabilities involve multiplication of the matrix for successive time periods.)

Computing Transition Probabilities and Expectancy Measures. As explained earlier, the impact of an educational program can be described in terms of the transitions of students from one instructional setting to another—for example, from special education to the mainstream program or to graduation. While each person's transition has important individual characteristics, we can summarize the entire set of transitions in terms of the proportions of students who move from one setting to another each year.

In principle, computing transition probabilities is a straightforward procedure that involves dividing the total number of students in each instructional setting at the start of a period into the individual totals moving from this setting to others by the end of the period. For example, if 40 of 80 students in a particular instructional setting graduate, the transition probability for graduation from this setting is 40/80, or .5. The matrix shown in Figure 1 would thus describe all transitions occurring during the period for the selected samples of students and instructional settings.

When we introduce other variables such as age, sex, type of handicap, and ethnicity, the calculations become somewhat more complex, since additional cells are added to the matrix. Where comparisons of the transition probabilities indicate differences due to such factors, it is necessary to subdivide the settings more precisely, requiring larger sample sizes. Based on our analyses, a minimum sample size of 1,500 to 2,000 students is required to discriminate among simple years of age and individual handicapping categories.

As described earlier, expectancy measures indicate likely educational attainments for particular ages. We can derive expectancy measures by multiplying transition probabilities successively, that is, calculating powers of the transition probabilities. These multiplications start from a base year and continue for 1 or more years into the future. By making these calculations, we were able to project educational expectancies for single years of age up to 21 years for students with different handicaps and assigned to different instructional settings.

Beginning of the Period \ End of the Period	SDC	RSP	DIS	Other	Unknown	M'Stream	Drop-out	Grad. Sch/work	Grad. No sch/work
SDC									
RSP									
DIS									
Other									
Unknown									
M'Stream									
Drop-out									
Grad. Sch/work									
Grad. No sch/work									

Figure 1. Structure of the MAP.

Compensating for the Small Size of the Pilot Test Sample. Ideally, our sample size would have been sufficiently large to empirically calculate transition rates for all cells in the matrix. However, we purposely restricted our pilot test to the high schools in a single school district, and therefore we had a relatively small data base with which to work. For example, when we added four age categories and three handicap categories to the structure of the basic matrix, it grew from 9 x 9 (81 cells) to 4 x 3 x 9 x 9 (or 972 cells). This stretched the limits of our small data base, creating many empty cells and cells with fewer than 10 or 20 total observations. Under these circumstances, we could not rely on the observed frequencies for every cell alone to obtain reliable transition probabilities. To solve this problem, we used log-linear analysis (described in the Technical Appendix) to produce estimated frequencies that we believe are more reliable than very small numbers of observed frequencies. We therefore used observed and estimated frequencies, depending on the cell sizes, using the following rule of thumb: Use observed frequencies when the total observations for a row of the matrix were greater than 30; use an average of the observed and estimated frequencies when the total was between 10 and 30 observations; use estimated frequencies when the total was less than 10. In this way, we obtained the most stable data that could have been produced from our small school district sample.

Because we were working with data for only two points in time, we estimated transition probabilities for successive years to obtain expectancy measures. In this case, we assumed that transition rates remain constant for pairs of years. We therefore used successive multiplications of the same matrix to produce the expectancy measures presented in the Results section below. We, of course, acknowledge that the assumption of stable transition rates is questionable, and we are currently attempting to validate this assumption. In addition, we estimated the variance associated with these expectancies to determine the reliability of the results. (See the Technical Appendix for a description of these analyses.)

RESULTS

Using the MAP to Project Educational Attainment

As explained earlier, the MAP uses data from management information systems to project the likelihood that students will move from one instructional setting to another over time (transition probabilities) and to project likely educational attainment by certain ages (educational expectancies). In designing the MAP, we gathered and manipulated the data to determine which data to include in the model and to produce a computer program that could analyze a variety of data and produce projections of educational attainment.

Significance of the Factors Affecting Transition Rates. When we ran analyses to determine the affects of age, handicap, sex, and ethnicity on transitional probabilities, we found age to be the only statistically significant factor. (The Technical Appendix includes a table showing the chi-squares associated with these variables.) In some sense the influence of age on transition within educational programs is not surprising: Students are more likely to be graduated as they grow older. In addition, learning disabled students—the group comprising the largest percentage of special education students and almost 80% of the pilot test group—may tend to be mainstreamed more often when they are younger; conversely, those who are not mainstreamed at an earlier age may be more likely to continue in special education for several more years. In any case, our results strongly suggest that any special education accounting system must differentiate among the ages of the students.

Although we did not find handicapping condition, sex, or ethnicity to be significant factors in determining transition, these variables should not be dismissed from analyses based on only these limited data; more studies of their effects on transitions in special education with larger sample sizes are warranted.

Illustrations of Some MAP Analyses. By gathering and manipulating the data from our pilot test, we designed a computer program that could generate a variety of projections, based on available information regarding students' instructional setting assignments, ages, and handicaps. By specifying these characteristics, we are able to project educational expectancies for single years of age up to 21 years. Table 1 presents these expectancies for a 15-year-old orthopedically disabled student, placed originally in a Special Day Class. This table is but one illustration of numerous expectancy tables the model can generate.

Similarly, we are able to generate figures that show relationships between different instructional setting assignments on projected mainstreaming, dropping out, and graduation rates of secondary students with particular handicaps at various ages. Figure 2, for example, illustrates the probabilities that orthopedically handicapped students in different instructional settings will be mainstreamed by age 17. We can produce similar tables and graphs for students with different handicaps and for other educational expectancies such as the probability of graduating and being at school or at work. (The methodology used to derive standard deviations for the estimated values is explained in the Technical Appendix.)

Observations from the Data. We believe our findings illustrate how the MAP can describe patterns of transitions and suggest likely outcomes for particular special education students over time. These patterns and projections, while by no means definitive, suggest ideas for further research on special educational transitions.

1. Students with orthopedic disabilities seemed to fare best when assigned to Designated Instructional Service. These students (a) were more likely to be mainstreamed at age 17, a likelihood that increased each year from 14 to 16 years of age; (b) had less chance of ever dropping out; and (c) had the best chance for work or postsecondary education following graduation. In general, however, the orthopedically disabled did not fare as well as learning disabled students, and fared only a little better than the retarded students.

2. For learning disabled students, no one setting consistently led to more desirable outcomes than others; the settings performed comparably in terms of providing mainstreaming opportunities, preventing withdrawal before gradua-

TABLE 1
EDUCATIONAL EXPECTANCIES FOR AN ORTHOPEDICALLY DISABLED STUDENT, AGED 15 YEARS, AND PLACED ORIGINALLY IN A SPECIAL-DAY CLASS[a]

At age 16—1 Year Later		
Chances of being—	In a Special Day Class	42.1%
	In a Resource Program	10.5%
	In a Designated Instructional Service	15.8%
	In some other special education setting	5.3%
	In special education, setting unknown	5.3%
	In a mainstream school setting	15.8%
	Dropped out of school	0%
	Graduated and at school or at work	0%
	Graduated but not at school or at work	5.3%
At age 17—2 Years Later		
Chances of being—	In a Special Day Class	17.8%
	In a Resource Program	15.2%
	In a Designated Instructional Service	2.5%
	In some other special education setting	8.4%
	In special education, setting unknown	8.4%
	In a mainstream school setting	15.4%
	Dropped out of school	3.2%
	Graduated and at school or at work	16.1%
	Graduated but not at school or at work	13.2%
At age 18—3 Years Later		
Chances of being—	In a Special Day Class	6.7%
	In a Resource Program	3.9%
	In a Designated Instructional Service	2.5%
	In some other special education setting	3.1%
	In special education, setting unknown	5.3%
	In a mainstream school setting	0.3%
	Dropped out of school	6.7%
	Graduated and at school or at work	50.2%
	Graduated but not at school or at work	21.7%
At age 19—4 Years Later		
Chances of being—	In a Special Day Class	2.9%
	In a Resource Program	1.6%
	In a Designated Instructional Service	1.4%
	In some other special education setting	1.4%
	In special education, setting unknown	2.2%
	In a mainstream school setting	0.3%
	Dropped out of school	8.2%
	Graduated and at school or at work	57.9%
	Graduated but not at school or at work	24.5%
At age 20—5 Years Later		
Chances of being—	In a Special Day Class	1.2%
	In a Resource Program	0.7%
	In a Designated Instructional Service	0.7%
	In some other special education setting	0.6%
	In special education, setting unknown	1.0%
	In a mainstream school setting	0.1%
	Dropped out of school	8.9%
	Graduated and at school or at work	61.5%
	Graduated but not at school or at work	25.7%

(continued)

TABLE 1
(CONTINUED)

At age 21—6 Years Later		
Chances of being—	In a Special Day Class	0.5%
	In a Resource Program	0.3%
	In a Designated Instructional Service	0.3%
	In some other special education setting	0.3%
	In special education, setting unknown	0.4%
	In a mainstream school setting	0.1%
	Dropped out of school	9.2%
	Graduated and at school or at work	63.1%
	Graduated but not at school or at work	26.2%

[a]These expectancies are based on data from one California school district.

tion, and promoting work or postsecondary education. Furthermore, learning disabled students fared better than other groups in terms of educational attainment.

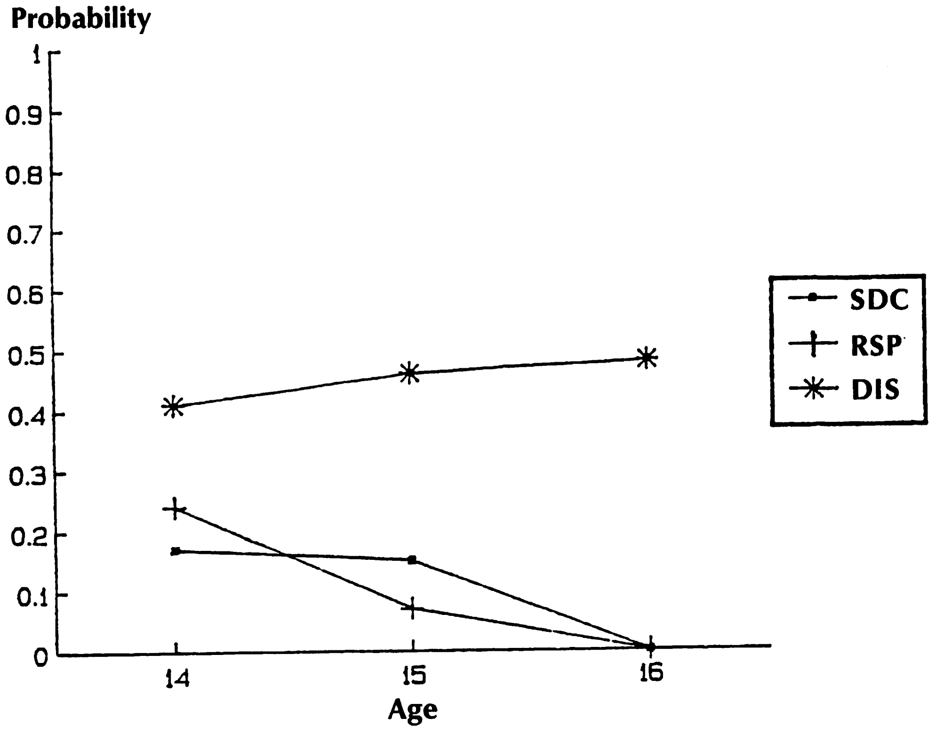
3. Retarded students and those with severe sensory disabilities also seemed to fare similarly following placements into any of the three settings, but fared less well than the other two groups. This group may continue to present the most challenging problems to special educators.

It is important to acknowledge again the limitations of such a small data base. We cannot use our data to make generalizations about the influence of placement or type of handicap on the attainment of individuals or groups of individuals; nor can we in any way prescribe preferred instructional assignments. We also recognize the important interaction between handicapping condition and instructional assignment. Obviously, IEP staff should place special education students in instructional settings based upon their handicap needs and available programs. If it appears, then, that students with particular handicaps are mainstreamed with greater frequency when placed in particular instructional settings, remember that these original assignments were based, at least in part, on IEP team recognition of the readiness of these students to be mainstreamed. Our results, in fact, reflect the effects of IEP placements made in the pilot test district.

DISCUSSION

The Model Accounting Plan is a distinctive way to track student participation in special education through the school years and after graduation. The MAP provides a more comprehensive picture of special education programs based on available management information than has been previously available. In fact, it is one of the first attempts to utilize transitional and follow-up data to address concerns related to student attainment. It has many potential benefits.

Most basically, the MAP provides a framework for considering management information data that describes the likely paths of special education students as they move through the school system and after they leave. Local educators need



Probabilities

Current Age	Special Day Class	Resource Specialist Program	Designated Instructional Service
14	.17	.24	.41
15	.15	.07	.46
16	.00	.00	.48

Standard Deviations

14	.06	.05	.07
15	.06	.03	.09
16	.03	.02	.16

Figure 2. Probability of being mainstreamed by age 17: Orthopedic Disability.

to know what happens to their students in order to assess the effectiveness of their programs; to gain insight into the relationships among student characteristics, instructional assignments, and attainments; and to estimate and allocate resources. Expectancy information provides useful feedback as well to the consumers of special education—namely parents who are concerned with the progress and well being of their children. For example, when either a Special Day Class or Resource Specialist Program placement might be advised for an orthopedically handicapped student, expectancies allow parents to see which type of program tends to lead to mainstreaming in the shorter term in a particular school district or region. Parents can thereby get a feeling for what the school system can provide their child and how the child might progress through the system. Similarly, policy makers at higher levels can use aggregated transitional data to ascertain trends and expectancies, and to gain a sense of how well special education programs are meeting their goals.

Further, the MAP data provide useful comparative information. For example, given the age of the child, parents and school officials might compare the prospects that alternative placements have for premature withdrawal or graduation. The data are useful for making other comparisons as well, such as comparing schools and school districts with similar populations and special education needs and services.

In addition, educators and decision makers at various levels can use MAP data to help assess the effectiveness of their programs in terms of their own goals and objectives. It is important to note that the special education goals of one school or school district may vary substantially from those of another district and that local goals may vary from state or federal goals. For example, while widespread mainstreaming might be the current goal of federal policy makers, local agendas might focus more on meeting the individual needs of special education students. Administrators can use expectancies to assess whether particular placements are leading to returns to regular programs or to dropping out for certain types of students. Similarly, teachers can measure how well they are doing in providing opportunities for graduation to their students. In these ways, transitional data can shed light on whether goals are being met or at least whether programs are on track in reaching goals.

Also, the MAP provides data that are useful for estimating resource needs and allocating resources. The federal government mandated pupil counts for the main purpose of resource allocation. Although simple counts have some use for estimating needs, transitional information based on these counts allows more accurate estimates of future needs at local, intermediate, and federal levels. For example, transitional estimates can be linked with data on resource use and costs to produce estimates of likely resource needs, given various transitional paths.

In the same vein, the MAP data allow administrators to make comprehensive reports to constituents at all levels: teachers to parents, principals to school boards, districts to state level administrators, and on up to Congress. A special education coordinator in our pilot test school district attributed her successful budget presentation to the school board to the preliminary MAP data we provided. Increasing demands for accountability from the top suggest that more quantitative information would strengthen the cause of special education as it competes for increasingly scarce resources.

Finally, the MAP data address several concerns of special educators, particularly the transitions from school to work, postsecondary education, and independent living. The data from a particular sample, large or small, can pose useful questions for further study. For example: Which aspects of an instructional setting seem to affect students with particular handicaps positively or negatively, in terms of postgraduation attainment? Why are students with certain disabilities more or less likely to be at work or in school following graduation than others? Which aspects of particular programs could be strengthened to ensure maximum benefits to students with particular handicaps?

Limitations of the MAP

Despite the potential benefits of the MAP, we cannot ignore the limitations of such a comprehensive, analytical model. These limitations have direct bearing on the feasibility of adopting and benefiting from such a system in the real world.

First, we acknowledge the extra burdens of collecting and analyzing the data at all levels. Although the MAP utilizes existing pupil count data and although most local school districts have various management information systems (MIS), extra burdens are involved in collecting additional transition data and in adapting existing MIS systems to the MAP. We suggested earlier that schools and districts perceive the current pupil count as burdensome and meaningless. Why, then, should they support a system that would demand even more of their limited resources? An incentive for participating is needed. We hope to develop incentives by demonstrating the potential of the MAP, by disseminating computer programs that support it, and by providing technical assistance to participants. Ideally, developing support for the MAP from state and federal administrators would assist this process.

In addition, the data required for the MAP to make specific statements about student progress limits its usefulness in small schools or school districts. Where numbers are small, we must group variables such as age and handicap. While the expectancies obtained from small samples are not as complete or meaningful as they are from larger populations, they can nonetheless shed light on the likely transitions of special education students in a school or district.

The MAP, in its preliminary state, is based on several questionable assumptions. First, it assumes that the data collected are accurate. Second, it assumes that transition probabilities remain stable over time. Pupil count data are inaccurate, we believe, because participants see no payoff in providing accurate numbers. If participants see the potential benefits of the MAP, we believe the likelihood of collecting more accurate data will increase. (We are currently assessing the stability of transition probabilities as part of Year 2 MAP.)

Finally, and most important, the MAP does not account for some vital human elements involved in the total special education picture. The system does not take into account variables that clearly affect transitions and attainment of special education students. Among these variables are individual differences among students, teachers, administrators, and schools or school districts (student-teacher ratios or time spent in programs, for example). In addition, the MAP cannot replace special education teachers, curriculum developers, and administrators in their critical roles of placing students, delivering services, and designing quality programs. Nor can the MAP compensate for inadequacies in these key people. The MAP, however, can help special education staff to understand better how students move within and beyond their programs and can help support their cause to administrators higher up.

Future of the MAP

To maximize the potential benefits and to address some of the critical limitations outlined above, we have continued to develop and refine the MAP. To validate the model with a full range of special education students, we have expanded the population of our pilot group to Grades K-12. To define our data more sharply, we have added the following variables to the model: vocational program offerings and specific types of DIS services, post-graduation earnings, and level of assistance from community agencies. As mentioned earlier, we are also assessing the validity of our assumption that transition rates are stable among pairs of years by comparing our Year 1 findings with Year 2 findings within the same school district. Finally, to facilitate widespread adoption of the MAP, we have designed easy-to-use MIS software that calculates transition probabilities and expectancies. Because the MAP builds on the annual pupil count of special education students, we have designed the software to handle all reporting requirements related to these counts and to allow also for entering and analyzing the follow-up data on recent graduates.

References

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TECHNICAL APPENDIX

1. *Using Log-Linear Analyses.* We used log-linear analysis procedures for two purposes: (a) to determine the effects of age, sex, ethnicity, and handicap on transition rates, and (b) to estimate transition rates when observed frequencies were too small—in other words, to compensate for small sample size. Log-linear analysis is based on fitting a log-linear model to observed cell frequencies. When a log-linear model is fitted to the observed frequencies in a table or matrix, the

TABLE A1
CHI-SQUARES ASSOCIATED WITH VARIOUS LOG-LINEAR MODELS

Model	Chi-square	*df*
Age and ethnicity[a]	.56	9
Age only	.86	12
Ethnicity only	95.96	18
Age and sex[a]	.20	9
Age only	1.93	12
Sex only	94.28	18
Age and handicap[b]	4.60	24
Age only	7.02	30
Handicap only	104.06	36

[a]Four categories of age and two categories of ethnicity (white and nonwhite) and sex.
[b]Five categories of age ("no age" and "missing age" were included as a single district category) and three categories of handicapping condition.

logarithms of the expected cell frequencies are written as additive functions of main effects and interactions, in a manner similar to the analysis of variance model. The statistical significance of particular factors for determining transition rates is thus measured by evaluating performance of the estimated models with and without these factors included. Table A1 shows the chi-squares associated with these factors by themselves and with each other.

We also used the results of log-linear analyses to produce estimated frequencies. These estimates are based on an overall structuring of the data such that the predicted value for any cell is determined through consideration of all the available data. We expect these model estimates to be more reliable for estimating transition probabilities than observed frequencies when the sample size is very small.

2. *Estimating the Variance of Projected Expectancies.* To estimate the variance associated with the projected expectancies, we used a procedure modeled after that presented by Kish and Frankel (1975). Specifically, we randomly divided the pilot test sample of 1,099 students into halves 10 times, creating 10 pairs of independent half-samples (samples of 550 and 549 persons, respectively). Next, we calculated expectancies for each half-sample. We then used the following formula to obtain the estimate of the variance of the expectancy, based on the full sample:

$$\hat{\sigma}^2_F = \frac{1}{2}\hat{\sigma}^2_H = \frac{1}{4n}\sum_{i=1}^{n}(b_{i1} - b_{i2})^2$$

where n is equal to the number of pairs of estimates based on half-samples (b_{i1}, b_{i2}), $i = 1, \ldots, n$. The standard deviations for the probability estimates based on the whole population appear in Figure 2 in the body of this article.