Evidence-based Organ Allocation*

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BACKGROUND: There are not enough cadaveric kidneys to meet the demands of transplant candidates. The equity and efficiency of alternative organ allocation strategies have not been rigorously compared.

METHODS: We developed a five-compartment Monte Carlo simulation model to compare alternative organ allocation strategies, accommodating dynamic changes in recipient and donor characteristics, patient and graft survival rates, and quality of life. The model simulated the operations of a single organ procurement organization and attempted to predict the evolution of the transplant waiting list for 10 years. Four allocation strategies were compared: a first-come first-transplanted system; a point system currently utilized by the United Network of Organ Sharing; an efficiency-based algorithm that incorporated correlates of patient and graft survival; and a distributive efficiency algorithm, which had an additional goal of promoting equitable allocation among African-American and other candidates.

RESULTS: A 10-year computer simulation was performed. The distributive efficiency policy was associated with a 3.5% ± 0.8% (mean ± SD) increase in quality-adjusted life expectancy (33.9 months vs 32.7 months), a decrease in the median waiting time to transplantation among those who were transplanted (6.6 months vs 16.3 months), and an increase in the overall likelihood of transplantation (61% vs 45%), compared with the United Network of Organ Sharing algorithm. Improved equity and efficiency were also seen by race (African-American vs other), sex, and age (<50 or ≥50 years). Sensitivity analyses did not appreciably change the qualitative results.

CONCLUSION: Evidence-based organ allocation strategies in cadaveric kidney transplantation would yield improved equity and efficiency measures compared with existing algorithms. **Am J Med. 1999;107:52–61.** ©1999 by Excerpta Medica, Inc.

Kidney transplantation is the treatment of choice for patients with end-stage renal disease, although the supply of cadaveric kidneys is insufficient to meet the demand. At the end of 1996, the waiting list for cadaveric kidney transplants had 34,550 candidates, whereas only 7,833 cadaveric transplants were performed during that year (1). Many educational and outreach efforts to increase the supply of donor organs have been unsuccessful. Any organ allocation algorithm must attempt to balance equity and efficiency without discriminating against groups of patients. We developed a decision analysis model to quantify this trade-off, considering alternative algorithms and several different ways to measure equity and efficiency.

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METHODS

Data Sources

The United Network of Organ Sharing (UNOS) Annual Reports provided data about the size of the waiting list for transplantation, the number of new transplants, and the number of deaths on the waiting list for each year between 1988 and 1994 (2). The United States Renal Data System (USRDS) 1995 Annual Report provided data about the incidence and prevalence of end-stage renal disease, along with mortality and cause-specific mortality rates stratified by age, sex, race, and primary renal disease for the years 1990 to 1992 (3). The 1994 Report of Center Specific Graft and Patient Survival (4) provided recipient- and donor-specific data on cadaveric kidney transplants performed between October 1987 and December 1991, including the following measurements: recipient age, sex, race, height, weight, blood type, and tissue type; diabetes; primary versus repeat transplant; number of pretransplant blood transfusions; peak and current panel reactivity; and functional status. Information was also obtained about donor age, sex, race, blood type, tissue type, and cause of death, as well as the donor kidney cold ischemia time.

Simulation Model

A Monte Carlo simulation model (Figure 1) of the operations of a single organ procurement organization was developed (5). The model attempts to predict the evolu-

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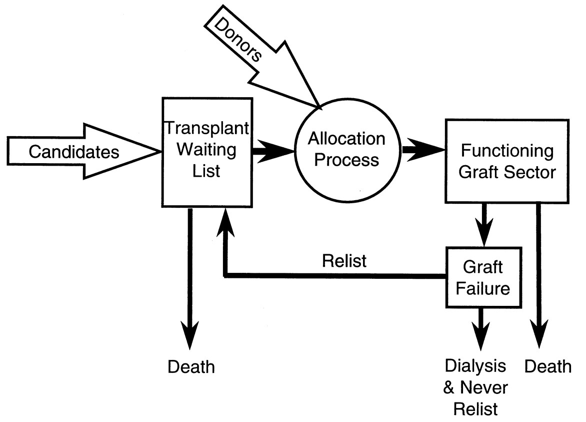

Figure 1. Schematic representation of the Monte Carlo simulation model.

tion of the transplant waiting list during 1995 to 2004 and anticipate the outcomes of the transplant and dialysis populations under alternative allocation policies. The simulation model contained five models within it: the Candidate Demographics model, the Waiting List model, the Donor Demographics model, the Organ Allocation model, and the Functioning Graft model.

The Candidate Demographics model generated first-time adult transplant candidates and their characteristics. For the candidate arrival rate, the model assumed that new patients arrived according to a random Poisson process (6) and that the rate increased with time to reflect the increasing numbers of patients with end-stage renal disease. Two arrival rates were considered: one that reflected a typical organ procurement organization, which was derived by dividing the national arrival rate and trend by the number of organ procurement organizations ($n = 73$), and one that reflected a congested organ procurement organization. Examination of new candidate arrivals during 1988 to 1994 demonstrated that the annual arrival rate increased at a linear rate of 327 candidates per year. An extrapolation of this rate indicated that there were 10,432 first-time waiting list registrants in 1995. From these figures we estimated that the arrival rate for the typical organ procurement organization was $\gamma(t) = 142.9 + 4.5 * t$ patients per year, and the arrival rate for the congested organ procurement organization was $\gamma(t) = 642.7 + 20.2 * t$ patients per year, where t is the time in years from 1995.

The model estimated the distribution of patient characteristics based on data from the UNOS Public Use Data Set (4) and the USRDS Annual Report (3). A comprehensive characterization of the distribution of patient characteristics would have required the computation of probabilities for more than 1.4×10^{11} combinations of clinical variables. Instead, we adopted an approximate procedure. First, we divided patients into four groups based on race and sex, and we estimated the relative frequencies for each group using the incidence rates of end-stage renal disease from the USRDS Annual Report. Second, we used the same report to estimate the relative frequencies for the different age categories within each of the four distinct sex-race groups. Third, we derived relative frequencies for blood type, panel reactivity, body surface area, and tissue type within each sex-race group using donor-specific data from the UNOS Public Use Data Set, assuming that within each sex-race group, the relative frequencies of blood type, panel reactivity, body surface area, and tissue type were the same in the donor and recipient pools (7). Finally, we generated characteristics of simulated patients by sampling according to the sex-race frequencies and then generating the patient's age, blood type, panel reactivity, body surface area, and tissue type using the remaining relative frequencies.

New transplant candidates joined the Waiting List model, where they remained until they either received an allograft or died. Monthly mortality on the Waiting List was estimated from the USRDS Annual Report stratified by age, sex, and race. We assumed a constant hazard rate for time on the waiting list within strata (8,9). Sensitivity analyses were performed to evaluate the influence of the constant-hazard assumption. The model assigned a utility of 0.6 for patients on the waiting list. In other words, their relative quality of life was assumed to be 60% of that for healthy individuals (10).

Patients who received an allograft entered the Functioning Graft model. They could exit this model after graft failure or death, which were assumed to occur independently. Patients who experienced graft failure either rejoined the Waiting List as repeat transplant candidates (with probability 0.75) or left the model. The utility of transplant status was assumed to be 0.75 (9). Mortality rates were estimated from the post-transplant mortality rates reported in the USRDS Annual Report. Graft failure was modeled with a proportional hazards model (11). In its derivation, data from the UNOS Public Use Data Set were utilized. Patients who were lost to follow-up, died with a functioning graft, or had a functioning graft on the last day of follow-up were censored. Missing data were categorized as "missing." A 3/4, 1/4 split random sample of the data was used to derive and validate the model.

Organ donors were generated by the Donor Demographics model. Because the supply of organs has been relatively constant and is not expected to increase substantially in the next decade, the model assumed that new donors arrived with two identical kidneys according to a random Poisson process with a constant arrival rate. The donor arrival rate in the typical organ procurement organization was 57.1 donors per year, and the rate in the congested organ procurement organization was 169.0 donors per year. Donor characteristics were generated by sampling with replacement the population in the UNOS Public Use Data Set (4).

The Organ Allocation model incorporated three phases: the mandatory sharing of zero-antigen mismatched kidneys, the chosen allocation algorithm, and the recipient kidney acceptance rate. To simulate the process of sharing zero-antigen mismatched kidneys among organ procurement organizations ("mandatory sharing"), we constructed a single national waiting list that aggregated the waiting lists of all organ procurement organizations except the one simulated by the model. The national waiting list was assumed to have a fixed size and known demographic composition. For each kidney procured by the local organ procurement organization, the model used the national waiting list to compute the probability of a blood group–compatible, zero-mismatched candidate in the national list, and then, with this probability, offered the kidney to that candidate. In addition, the model simulated a national donor pool, and for each donor tested for the presence of zero-mismatched candidates in the local organ procurement organization. The national donor pool was simulated in the same manner as the local donor pool, but with a donor arrival rate equal to the national arrival rate minus the local arrival rate. Finally, if the number of kidneys that the local organ procurement organization had sent to the national waiting list was not equal to the number of kidneys that it had received, then the local organ procurement organization either received the next kidney procured by the national list or sent the next kidney that it procured locally until the imbalance was corrected.

Allocation Policies

We describe the results of four allocation policies for rationing kidneys among blood group–compatible candidates on the local transplant waiting list: a first-come first-transplanted strategy; the UNOS algorithm (a point system utilized by UNOS since August 1995; Table 1); an efficiency-based algorithm, designed to maximize quality-adjusted life expectancy (Table 2); and a distributive efficiency algorithm, the additional goal of which was to promote equitable allocation among African-American and other candidates.

In the efficiency and distributive efficiency algorithms, the highest priority candidate was the one with the greatest increase in quality-adjusted life expectancy if transplanted. For each candidate and organ, this was calculated as the quality-adjusted life expectancy assuming a transplant (but no retransplant after graft failure) minus the quality-adjusted life expectancy assuming no transplant and no future transplant. (Because these estimates do not account for future transplants, algorithms employing more elaborate calculations might improve estimated quality-adjusted life expectancy.)

To determine the priorities for each transplant candidate, the efficiency-based algorithms estimated the graft failure hazard rates (11) and the mortality rates, which were derived from the data in the simulation model. Accordingly, patients with greater hazard rates (ie, greater relative risks) were given lower priority for transplant. Sensitivity analyses were performed to examine the performance of the efficiency-based algorithms, biasing the model assumptions in favor of the UNOS algorithm.

Table 1. The United Network of Organ Sharing (UNOS) Point System

Category	Points
Waiting time	1 (0.5) point for each full year on the waiting list
Rank in the waiting list	1 (1) point for the longest waiting candidate; fractions of points are assigned proportionately to all other candidates
Tissue mismatches	infinite (10) for no mismatches
	7 (7) points for no B or DR mismatches
	0 (6) points for no A or B mismatches
	5 (3) points for 1 B or DR mismatch
	2 (2) points for 2 B or DR mismatches
	0 (1) point for 3 B or DR mismatches
Panel reactivity	4 (4) points for panel reactive antibody >80%
Pediatric candidates	4 (2) points when age <11 (5) years
	3 (1) points when 11 (5) < age < 18 (10) years

* Points or values in parentheses were used before July 31, 1995.

The major factors that affected the priority rankings for the efficiency-based algorithms were recipient age, sex, and race, panel reactivity, body surface area, tissue matching, and previous transplant (Table 2). For example, because the relative risk of graft failure is greater among African-Americans, the increase in quality-adjusted life expectancy if transplanted is lower in African-Americans than in other patients. Therefore, assuming that all other factors were the same, the efficiency algorithm would assign lower priorities to African-American candidates. The distributive efficiency algorithm eliminated the race component from the priority rankings by assuming that the risk of graft failure is identical for both major racial groups. In contrast, the only factors that influenced the UNOS algorithm were tissue matching, panel reactivity, and waiting time.

Within all allocation strategies, a kidney was offered to the highest priority blood group–compatible candidate. If the candidate was available and cross-matched negative, the transplantation was performed. Otherwise, the kidney was offered to the next candidate and the procedure was repeated until an available candidate that cross-matched negative was found. The model used three probabilities to simulate the acceptance process: the probability that a presensitized candidate would cross-match negative, the probability that a nonpresensitized candi-

Table 2. Factors Incorporated into the Efficiency Policies

Factor (comparison)	Priority Ranking	Relative Risk of Graft Failure (95% confidence interval)
Recipient and donor gender (female organs to female recipients)	Other combinations	1.12 (1.06, 1.18)
Recipient race (other)	African-American	1.57 (1.44, 1.61)
Recipient age (≥50 years)	≤50 years	1.14 (1.02, 1.25)
Panel reactivity [nonpresensitized (panel reactive antibody <0.60)]	presensitized (panel reactive antibody ≥0.60)	1.47 (1.37, 1.57)
Body surface area (<2.00 m^2)	≥2.00 m^2	1.10 (0.99, 1.21)
Prior transplants (none)	One or more prior transplants	1.29 (1.21, 1.37)
HLA mismatch (zero)	one mismatch at A, zero at B and DR	1.09 (0.98, 1.20)
	one mismatch at DR, zero at A and B	1.10 (0.99, 1.21)
	two mismatches at A, zero at B and DR	1.13 (1.02, 1.24)
	one mismatch at B, zero at A and DR	1.21 (1.10, 1.32)
	one mismatch at A, one mismatch at DR, zero at B	1.21 (1.10, 1.32)
	two mismatches at DR, zero at A and B	1.28 (1.17, 1.39)
	two mismatches at B, zero at A and DR	1.30 (1.19, 1.41)
	more than two mismatches	>1.30 (1.19, 1.41)

date would cross-match negative, and the probability that the candidate would be available. The first two probabilities were estimated as 0.15 = 1 − (average panel reactive antibody of all presensitized recipients in the period October 1987 to December 1991) and 0.92 = 1 − (average panel reactive antibody of all nonpresensitized recipients in the same period), respectively. These probabilities were somewhat underestimated, because the panel reactive antibody estimates the probability that a candidate will cross-match positive with a randomly selected donor. In practice, donors were not randomly selected (eg, a zero-mismatched, mandatory shared kidney). The probability that a candidate was available was estimated at 0.42 (12).

Simulation Run

For each policy, the organ procurement organization was simulated for 10 years. The initial states of the Waiting List and Functioning Graft models for the first year of the simulation were obtained as follows: the typical organ procurement organization and the congested organ procurement organization were simulated simultaneously starting from empty Waiting List and Functioning Graft models under the UNOS policy. Both simulations were terminated when the size of the waiting list in the typical organ procurement organization reached 380 (equal to 1/72 of the national waiting list at the end of 1994, given 72 organ procurement organizations in the United States). Baseline characteristics of the dialysis and transplant recipient populations are described elsewhere (2,3,5,11).

Outcome Variables

The principal outcome measures of the simulation included patient survival, quality-adjusted life expectancy, median waiting time, and likelihood of transplantation. The estimates of quality-adjusted life expectancy and the likelihood of transplantation did not account for the remaining lifetime of patients who were alive at the end of the 10-year simulation. To investigate whether this introduced bias into the comparisons of the different policies, an additional 100-year simulation was performed for each policy. (The major results presented in this report are from the 10-year runs, but differences with 100-year runs are also discussed.) Results were obtained for the overall population, as well as for subjects stratified by race (African-American vs other), sex, and age (<50 vs ≥50 years), and expressed as absolute and percentage values. We estimated 95% confidence intervals for the performance measures by performing 40 independent simulations, starting from the same initial conditions. Kaplan-Meier techniques were used to estimate survival (13).

Sensitivity Analyses

Additional simulations were performed, modifying the assumptions made to generate graft failures and patient death. The assumptions used to estimate the increase in quality-adjusted life expectancy for each candidate and organ were not altered, so these analyses assess the impact of erroneous assumptions within the distributive efficiency algorithm. The focus was on assumptions that would lead to differences in allocation outcomes among the UNOS policy and the efficiency-based policies; thus, the modifications were consistent with historical data and were biased in favor of the UNOS algorithm. For example, the relative risk of graft failure associated with prior transplant was reduced from 1.29 to 1.21. For each of the factors that affected graft failure and that were treated differently by the UNOS and the efficiency-based algo-

Table 3. Summary Inputs for the Simulation Models

Parameter	Age		Sex		Race	
	<50 years	≥50 years	Male	Female	African-American	Other
Median survival on waiting list (years)	6.5	2.1	2.9	3.2	3.5	2.7
Median survival after transplantation (years)	33.0	8.7	11.1	13.3	11.0	13.3
Median graft survival (years)	5.2	5.7	5.3	5.1	4.1	5.9

rithms, we reduced the relative risk of graft failure to the lower bound of the 95% confidence intervals in the proportional hazards model (Table 2). In addition, we modified the assumption of a constant mortality on the waiting list and considered four scenarios of increasing hazard. These scenarios assumed that each additional year on the waiting list was associated with a 2.5%, 5%, 10%, or 20% increase in mortality. In an additional scenario, all of the relative risk estimates for graft failure were simultaneously biased in favor of the UNOS algorithm, and mortality on the waiting list was assumed to increase at a rate of 5% per year.

RESULTS

Patient Survival

A summary of the effects of age, sex, and race on survival on the waiting list, survival after transplantation, and graft survival is presented in Table 3. Five-year survival rates were 69.6% in the distributive efficiency policy, 69.0% in the efficiency policy, 63.5% in the UNOS policy, and 64.1% in the first-come first-transplanted policy (Figure 2). When stratified by race, the 5-year survival rates for non–African-American patients were 70.4%, 72.0%, 62.7%, and 62.5% in the corresponding groups. In contrast, the 5-year survival rates for African-American patients were 67.7% in the distributive efficiency policy, 61.7% in the efficiency policy, 65.5% in the UNOS policy, and 67.8% in the first-come first-transplanted policy. Under the first-come first-transplanted policy, African-Americans had greater overall 5-year survival because they had lower mortality rates on dialysis than other patients.

Long-term survival was greater in women than men (Figure 3). Estimated survival was greater with the distributive efficiency and efficiency policies than with the

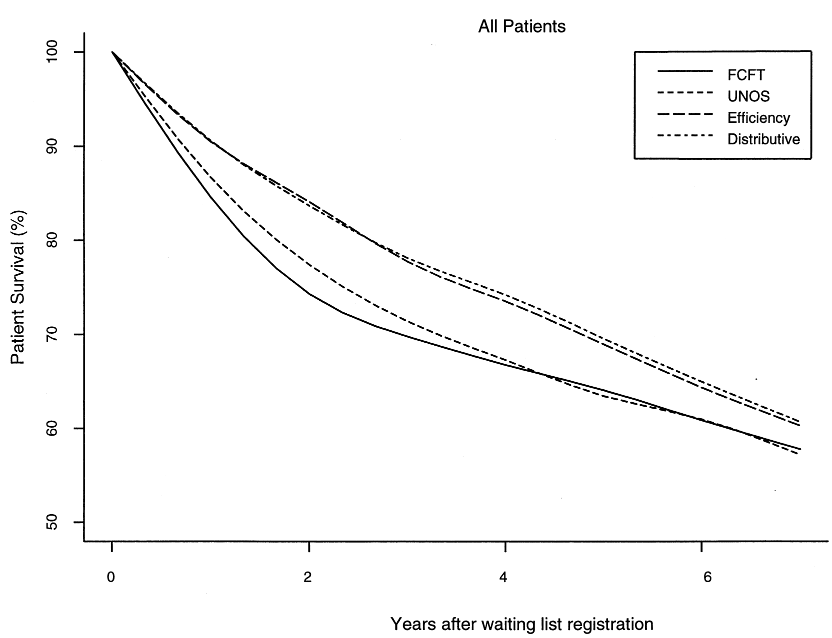

Figure 2. Survival of transplant candidates by allocation algorithm. Survival curves were estimated from the outcomes of the first simulation run using the Kaplan-Meier product limit method. Patients who were alive on the last day of the simulation run contributed right-censored observations. FCFT = first-come first-transplanted policy.

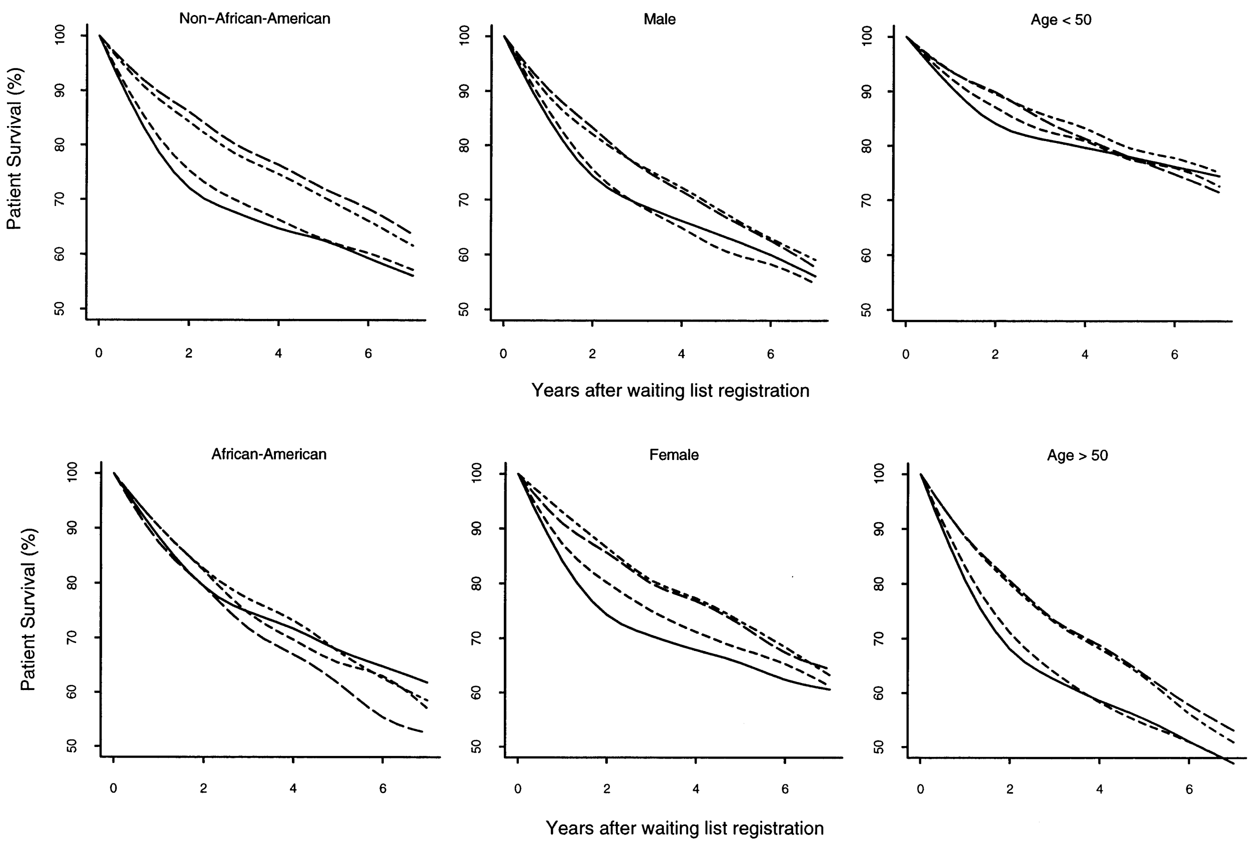

Figure 3. Survival of transplant candidates by allocation algorithm and demographic characteristics.

UNOS and first-come first-transplanted policies in both sexes throughout the simulation period.

As expected, survival was better among patients younger that 50 years compared with older patients (Figure 3). For patients 50 years of age or older, the distributive efficiency and efficiency policies yielded better survival than the UNOS and first-come first-transplanted policies. In contrast, for patients younger than 50 years, there were no appreciable differences in survival among the four policies.

Quality-adjusted Life Expectancy

The overall quality-adjusted life expectancy was 33.9 ± 0.1 months in the distributive efficiency policy (mean ± 95% confidence interval), 34.2 ± 0.1 months in the efficiency policy, 32.7 ± 0.1 months in the UNOS policy, and 32.6 ± 0.1 months in the first-come first-transplanted policy. Using the UNOS policy as the reference, the relative change in quality-adjusted life expectancy was 3.5% for the distributive efficiency policy, 4.5% for the efficiency policy, and −0.2% for the first-come first-transplanted policy (Figure 4). The relative change in quality-adjusted life expectancy depended on race, sex, and age: for African-Americans patients, the efficiency policy yielded a −7.2% decrease in quality-adjusted life expectancy, whereas for other patients the efficiency policy yielded a 9.8% increase in quality-adjusted life expectancy. In contrast, the distributive efficiency policy yielded a 0.8% increase in quality-adjusted life expectancy in African-American patients and a 4.9% increase in other patients.

The efficiency and distributive efficiency policies also resulted in 3% to 5% increases in quality-adjusted life expectancy for men and for women (Figure 4). By contrast, there were no differences in the quality-adjusted life expectancy associated with the efficiency and distributive efficiency policies for patients younger than 50 years, whereas older patients had 7% to 9% greater quality-adjusted life expectancy with the distributive efficiency and efficiency policies because of the more frequent use of transplantation with these strategies.

Waiting Time to Transplant

Median waiting times to transplantation among those who are transplanted were 6.5 ± 0.3 months in the distributive efficiency policy, 4.9 ± 0.3 months in the efficiency policy, 16.3 ± 0.4 months in the UNOS policy, and 20.5 ± 0.4 months in first-come first-transplanted policy.

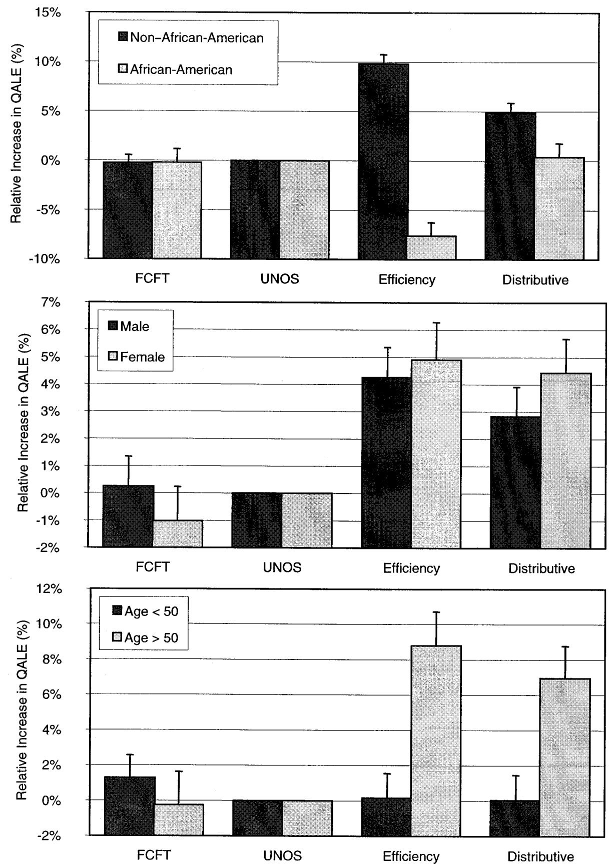

Figure 4. Relative increase in quality-adjusted life expectancy (QALE) by race (**top panel**), sex (**middle panel**), and age (**bottom panel**). The **bars** indicate the relative increase in quality-adjusted life expectancy compared with UNOS for each demographic group under the first-come first-transplanted (FCFT), efficiency, and distributive efficiency algorithms. In the top panel the **dark bars** indicate non–African-Americans and the **light bars** indicate African-Americans. In the middle panel the **dark bars** indicate men and the **light bars** indicate women. In the bottom panel the **dark bars** indicate candidates younger than 50 years old and the **light bars** indicate candidates older than 50 years. The error bars are 95% confidence limits.

Under the efficiency algorithm, the median waiting time for African-American patients was increased compared with UNOS, whereas the median waiting time for other patients was substantially decreased (Figure 5). The distributive efficiency model yielded moderate decreases in median waiting times for both races.

The median waiting times for men and for women were similarly decreased in the efficiency and distributive efficiency policies. The median waiting time for older patients was decreased with the efficiency and distributive efficiency policies, with somewhat less reduction among younger subjects in the distributive efficiency policy, because of the higher priority given to older subjects under this algorithm (Figure 5).

Likelihood of Transplantation

The likelihood of transplantation is defined as the fraction of transplant candidates who received at least one transplant during the 10-year period. Under the efficiency and distributive efficiency policies, priority was given to primary transplant candidates, so that a greater proportion of candidates (compared with UNOS or first-come first-transplanted) received a primary transplant, whereas fewer received two or more transplants. The likelihood of transplantation was 60.9% in the distributive efficiency policy, 61.8% in the efficiency policy, 44.8% in the UNOS policy, and 45.5% in the first-come first-transplanted policy (Figure 6). As expected, the curves for the first-come first-transplanted policy increased over time, indicating a greater likelihood of transplantation with in-

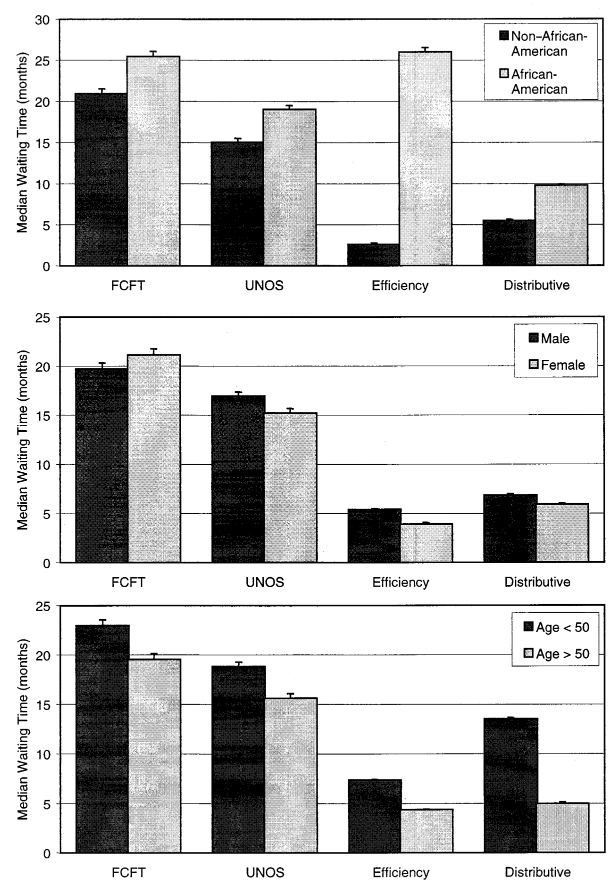

Figure 5. Median waiting time by race (**top panel**), sex (**middle panel**), and age (**bottom panel**). The **bars** indicate the median waiting time for each demographic group under the four allocation algorithms: first-come first-transplanted (FCFT), UNOS, efficiency, and distributive efficiency. In the top panel the **dark bars** indicate non–African-Americans and the **light bars** indicate African-Americans. In the middle panel the **dark bars** indicate men and the **light bars** indicate women. In the bottom panel the **dark bars** indicate candidates younger than 50 years and the **light bars** indicate candidates older than 50 years. The error bars are 95% confidence limits.

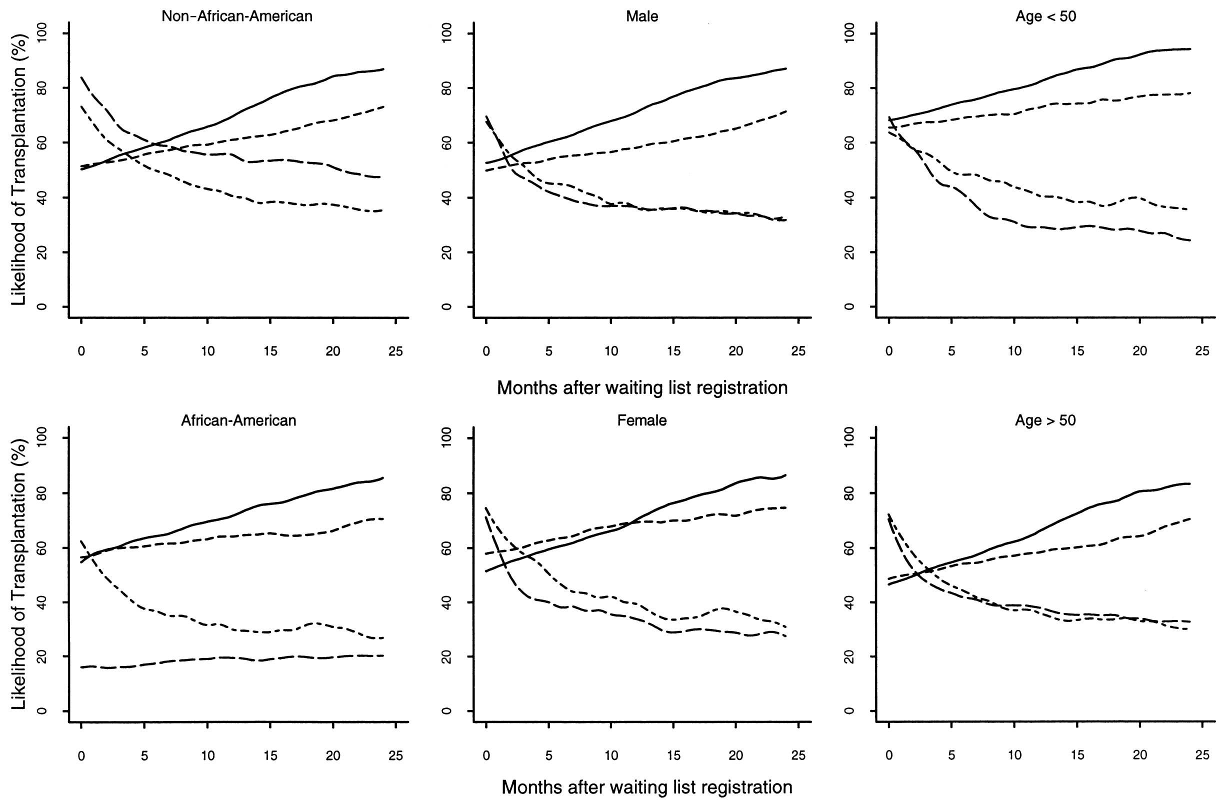

Figure 6. Likelihood of transplantation by allocation algorithm and race, sex, and age. The likelihood of transplantation is the probability that a candidate will receive an allograft during his or her lifetime.

creasing time on the waiting list. In general, the results with UNOS policy were similar to the first-come first-transplanted policy, because of the effect of waiting time points in the allocation algorithm. In contrast, the distributive efficiency and efficiency policies were associated with a decreased likelihood of transplantation with time, because of selection of patients within the groups who have the most favorable characteristics.

Sensitivity Analyses

An underestimate of the relative risk of the risk factors for graft failure diminished the improvement achieved by the distributive-efficiency algorithm by no more than 0.3 months, or 25%. If all of the factors were simultaneously underestimated, the performance improvement would be diminished by 0.6 months, or 50% (Table 4). The results were sensitive to the assumption of a constant mortality on the waiting list. If mortality increased with time, the improvement achieved by the distributive efficiency algorithm would have been diminished (Table 4). However, mortality would need to increase by at least 20% per year for the distributive efficiency and the UNOS policies to yield similar results. The effects on 5-year survival rates were similar. However, median waiting times were insensitive to any of the model assumptions that were tested.

In the 100-year simulations, the quality-adjusted life expectancy was 41.4 ± 0.1 months in the distributive efficiency policy, 42.1 ± 0.1 months in the efficiency policy, 38.5 ± 0.1 months in the UNOS policy, and 38.2 ± 0.1 months in the first-come first-transplanted policy. Using the UNOS policy as the reference, the relative change in quality-adjusted life expectancy was 7.5% for the distributive efficiency policy, 10.2% for the efficiency policy, and −0.8% for the first-come first-transplanted policy. Thus, the 10-year simulations somewhat understated the advantages of the efficiency-based algorithms.

The Congested Organ Procurement Organization

Although the qualitative results did not change, there were substantial quantitative differences between the typical organ procurement organization and congested organ procurement organization scenarios. The median waiting times were longer for all algorithms (average increase of 20 months) in the congested organ procurement organization, as would be expected. Patient survival was decreased (average decrease 22.3% at 5 years), whereas graft survival was slightly greater (average increase 2.8%), because of the larger pool of transplant candidates with optimal characteristics.

Table 4. Influence of Parameter Uncertainty on the UNOS and Distributive Efficiency Policies: Model Parameters Biased in Favor of UNOS

Assumption	UNOS			Distributive Efficiency		
	Quality-adjusted Life Expectancy (months)	Median Waiting Time (months)*	Five-year Survival (%)	Quality-adjusted Life Expectancy (months)	Median Waiting Time (months)*	Five-year Survival (%)
Base case	32.7	16.3	63.5%	33.9	6.5	69.6%
Bias in the relative risks of graft failure						
Gender	32.9	17.0	64.5%	33.8	6.5	68.6%
Age	31.7	16.5	58.2%	32.7	6.7	63.4%
Panel reactivity	32.6	15.9	62.7%	33.5	6.6	67.6%
Body surface area	32.9	16.3	64.5%	33.8	6.6	68.6%
Prior transplant	32.7	16.0	63.8%	33.6	6.8	68.2%
Bias in the waiting list mortality hazard						
Waiting time (hazard increase of 2.5% per year)	32.8	16.3	64.0%	33.5	6.5	67.2%
Waiting time (hazard increase of 5% per year)	33.1	16.4	66.0%	33.7	6.5	68.7%
Waiting time (hazard increase of 10% per year)	33.3	16.3	66.7%	33.8	6.5	69.0%
Waiting time (hazard increase of 20% per year)	33.7	16.8	68.7%	33.7	6.6	68.4%
Simultaneous changes in all relative risks and waiting list hazard increase 5% per year	32.0	16.6	60.3%	32.6	6.5	63.2%

* Among those who receive a transplant.
UNOS = United Network of Organ Sharing.

DISCUSSION

The efficiency-equity tradeoff in cadaveric kidney transplantation can be alleviated by decreasing the demand–supply ratio, reducing demographic- and nondemographic-based differences in patient and graft survival rates, and employing an organ allocation policy that explicitly addresses this trade-off. The first approach requires changes in the legal system (eg, presumed consent) or biology (eg, changes in the incidence of end-stage renal disease), whereas the second approach requires major advances in the care of transplant patients. Because these changes are not expected to be achieved in the foreseeable future, we have analyzed the third approach, the only one that might influence the efficiency-equity trade-off in the next few years. In this report, we describe a Monte Carlo simulation model that compares alternative organ allocation policies. Two measures of equity (waiting time and likelihood of transplantation) and two measures of efficiency (patient survival and quality-adjusted life expectancy) were compared among transplantation policies.

Equity is an elusive concept. The measures of equity that we used focused on variations among demographic groups (race, sex, and age) rather than variation within groups. We attempted to quantify equity by comparing median waiting time and likelihood of transplantation, aiming to reduce variation between groups of patients. Alternative measures of equity, such as those based on economic models of social welfare, could also be considered.

It is difficult to assess inequity without a reference point that represents a perfectly equitable policy. There are two natural candidates for gold standards: the first-come first-transplanted policy and a hypothetical but unachievable policy that equalizes all equity measures in all demographic groups. The first-come first-transplanted policy does not treat different demographic groups identically. It is subject to prescreening for blood group incompatibility and sensitization, and there are important demographic differences in survival rates of patients on dialysis (ie, improved survival for African-Americans) along with variable demand-supply ratios (ie, fewer African-American donor kidneys). The policy currently used by UNOS is not appreciably more efficient, in terms of quality-adjusted life expectancy, than a first-come first-transplanted policy. Hence, if one views quality-adjusted life expectancy as the primary efficiency measure and adopts a first-come first-transplanted policy as the gold standard for equity, then first-come first-transplanted policy is preferable to UNOS, regardless of the relative importance of efficiency and equity.

For the population at large, the efficiency policy yields the largest gains in quality-adjusted life expectancy. However, its adoption may be unattractive, because the improvement in quality-adjusted life expectancy is partly gained at the expense of African-American patients. Consequently, the efficiency policy was modified to counter this efficiency-induced discrimination. Using our efficiency and equity metrics, the distributive efficiency algorithm yielded an increase in quality-adjusted life expectancy that is roughly 65% of the estimated improvement achieved by the use of cyclosporin (14), and comparable to what would be achieved by a 23% increase in the supply of donor organs. Much of the efficiency gains were achieved by employing demographic (eg, favoring female-to-female transplants) and nondemographic (eg, discouraging retransplantation) factors that are not included in the UNOS policy. The resulting distributive efficiency policy was superior to the point-system policy currently employed by UNOS.

Other characteristics of transplant candidates may also influence the likelihood of success after kidney transplantation. For instance, a previous kidney transplant increases the graft failure rate, and would contribute to a lower priority for allocation in any efficiency-based model. Policy makers will have to decide which patient characteristics warrant subsidy if efficiency is to be compromised in favor of a more equitable distribution of organs.

Our simulation model has several limitations. More precise estimates of mortality among wait-listed patients could be made if additional clinical information were utilized. Better estimates of graft survival could also be made if additional data relevant to the pretransplant course (eg, general health preceding transplantation, duration of dialysis therapy, and nutritional status) were available.

Extensive sensitivity analyses of the model assumptions did not appreciably change our qualitative findings. One possible exception is the effect of a substantially increased mortality among patients on the waiting list. However, this would imply that the hazard of death for someone who has been on the waiting list for 4 years is twice that of someone who was just listed, which we consider to be unrealistic. Furthermore, simulations that eliminated the influence of censored observations showed that the relative superiority of the efficiency-based algorithms was maintained, or even strengthened, with longer follow-up. Given the rapid evolution of immunosuppressive therapy and other transplantation technology, we believe that it is reasonable to report results for a relatively short time period of 10 years.

Promoting effective and equitable organ allocation is one of the priorities of the current Secretary of the Department of Health and Human Services, Donna Shalala, who called for the development of "medically objective new criteria that would help to ensure a 'level playing field' in selecting among patients and determining which have the greatest medical need" (15) and for organ allocation policies that "give priority to those whose needs are most urgent, thereby reducing differences in waiting times for patients of like medical status." Application of such a policy in renal transplantation (where an alternative therapy, dialysis, is available) would result in an increase in overall waiting times and lower patient and graft survival. We agree that medical objectivity is desirable and suggest that available evidence be used to guide policy development.

Devising an effective and fair organ allocation policy involves difficult choices, such as the relative importance of equity and efficiency. Although any policy will inevitably be disadvantageous to some patients, it is possible to develop evidence-based policies that simultaneously improve health outcomes for all patients with end-stage renal disease. However, a recommendation for revising the current allocation policy can only be successful if it meets the stringent requirements of public approval.

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