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Background

- > Patient-level correlation analyses are essential to validate the **prognostic value of a candidate surrogate outcome**[1-3], and thereby guide decision-makers when data for the target outcome remain immature
- Bivariate copula functions provide an intuitive approach to jointly model associated survival outcomes, such as progression-free (PFS) and overall survival (OS) in oncology studies, via linking a pair of marginal distributions[4-6]
- > Consideration of parametric distributions for both the marginal survival and copula functions leads to an excessive number of candidate models that is unfeasible to assess in practice

Objectives

> We explored **trends in stability** of estimated rank correlation coefficients (Spearman's rho) and shortterm extrapolations to the marginal distributions and copula function in bivariate survival models, to establish feasible model selection procedures

Methods

- > We employed one of seven standard models[7] for the choices of both marginal distributions and one of six selected copulas encompassing diverse association patterns[8,9] to represent correlation
 - statistical goodness-of-fit was assessed by the Akaike Information criterion (AIC)
- > Bivariate copula models were applied to synthetic data emulating PFS-OS outcomes in a phase III study of patients with metastatic colorectal cancer treated with FOLFOXIRI plus bevacizumab[10]
 - > median follow-up duration was 31.0 months and association was moderate (Spearman's rho ≈ 0.5)
 - progression events, with observed (50.4%) or censored (34.1%) OS events, were observed for a majority of patients (N=252)

Conclusions

Selection and stability of parametric bivariate copula models for joint modelling of overall and progression-free survival

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Results

- > Extrapolated 5-year OS was generally robust to the choice of copula but was sensitive to the choice of marginal distribution (Tables 1 & 2)
- > For all choices of marginal distributions, the Hougaard copula gave the best fit, followed by the Joe and Gaussian copulas (Table 2)

the single best-fitting model was based on loglogistic marginals, but the preferred marginal model varied across the copulas

- Spearman's rho was sensitive to the choice of both marginal and copula distributions
 - however, when **restricting to the four** marginal models that gave the most reasonable independent fits (i.e., AIC within 5 points [Table 1]), estimates for Spearman's rho were highly consistent (Table 2)
 - in general, robustness of Spearman's rho is expected when marginal models give a sufficiently accurate fit
 - hence, the preferred marginal distributions for PFS and OS could have been decided appropriately based on the independent fits, following the conventional selection process[7]
- > For chosen marginal distributions, the preferred copula function should be selected based on a combination of goodness-of-fit (AIC or more sophisticated metric) and the clinical plausibility of its description of the impact of progression on death events (Fig. 1)
 - across bivariate models based on log-logistic marginals, estimated 12-month OS for patients who had progressed disease within 6 months was greatest for the Clayton copula (68.4%) [95% confidence interval (CI): 59.0-74.5%] vs 54.3% [95% CI: 43.1-64.7%] Hougaard)
 - such analyses offered by copula models enable individualized prediction for high-risk **patients**, provided that appropriate copula and marginal functions are selected

> This study supports a two-step selection procedure for bivariate survival models, where the marginal distributions are chosen by independent fits and are subsequently re-optimized under the copula likelihood

Bivariate copula models should be used more routinely to yield detailed clinical insights on patient-level correlation of survival outcomes and thereby support assessment of candidate surrogate endpoints

employing the candidate set of representative copula functions used here, and critiquing the clinical plausibility of conditioned OS distributions during the model selection process, alleviates issues of sensitivity and assumptions on correlation structure that have been criticized in previous work[6]

Figure 1: OS, and OS conditioned for patients whose time to progression is <6 months (N=41), estimated from bivariate models based on log-logistic marginal distributions linked by various copula functions.



Table 1: Summary of estimates obtained from bivariate models by marginal distribution, under a range of copulas.

Marginal distribution	Avg. rank	Range of $ ho_{ m S}$	$ ho_{ m S}$ (Hougaard) [95% CI]	∆AIC (Hougaard)	ΔAIC (indep.)	Range of 5-year OS (%)
Exponential	6.0	0.53-0.67	0.61 [0.52-0.69]	28.1	31.7	19.6-24.1
Weibull	3.3	0.40-0.54	0.46 [0.36-0.58]	5.9	1.1	16.2-17.3
Gamma	1.8	0.37-0.54	0.42 [0.31-0.54]	1.9	1.5	17.4-19.4
Gompertz	5.0	0.45-0.58	0.53 [0.42-0.64]	22.3	10.4	7.6-12.6
Log-normal	7.0	0.34-0.60	0.45 [0.33-0.57]	29.6	52.0	25.6-29.4
Log-logistic	2.8	0.31-0.53	0.40 [0.29-0.53]	0.0	4.3	22.3-25.3
Gen. gamma	2.0	0.37-0.53	0.43 [0.32-0.55]	4.1	0.0	5.4-14.5

Table 2: Summary of estimates obtained from bivariate models by copula function, under a range of marginals.

Copula	Avg. rank	Best marginal	Range of $ ho_{ m S}$ [restricted range]	$ ho_{ m S}$ (log-logistic) [95% CI]	ΔAIC (log- logistic)	Range of 5-year OS (%)
Clayton	4.4	Gen. gamma	0.43-0.57 [0.43-0.48]	0.48 [0.36-0.61]	42.8	7.6-29.4
Frank	5.7	Gen. gamma	0.42-0.57 [0.42-0.45]	0.45 [0.33-0.58]	49.1	5.4-28.8
Gaussian	3.0	Gamma	0.53-0.67 [0.53-0.54]	0.53 [0.41-0.61]	13.9	10.9-27.7
Hougaard	1.0	Log-logistic	0.40-0.61 [0.40-0.46]	0.40 [0.29-0.53]	0.0	12.1-25.6
Joe	2.0	Log-logistic	0.31-0.54 [0.31-0.40]	0.31 [0.22-0.43]	3.2	12.6-25.6
Plackett	4.9	Gamma	0.42-0.56 [0.42-0.45]	0.45 [0.32-0.56]	46.1	9.5-26.9

 $\Delta AIC = relative Akaike information criterion; <math>\rho_S = Spearman's$ rho; CI = confidence interval; OS = overall survival

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