
CHATGPT 100,000 PATIENT 24-MONTH *In Silico* PHASE III 5-ARM PANCREATIC CANCER CLINICAL TRIAL TRIPLICATE

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July 24, 2025

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Prompt 33

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ChatGPT o3-pro Research Generation: 25 Pages, July 9, 2025

“Trial 2”

Note: 30/30 Images in S39.VIS.01.P33.IMAGES

Prompt 33:

You have access to the full simulated PDAC Cancer 100,000-patient Phase III clinical trial log file with the following columns: patient_id, arm, archetype, age, stage_iv, ecog, kras_g12c, gbrca, ca19_9, time_to_progression_or_death, time_to_death, and time_to_first_G3_AE. Generate the following 30 visualizations as separate PNG files in one folder, ensuring each plot is clearly titled and labeled. The control arm is Arm E.

List of 30 Visualizations:

1. Bar chart of patient counts per treatment arm, to confirm balanced randomization across all five arms.
2. Overlaid density plots of patient age distribution for each treatment arm, to visualize and compare the age profile across cohorts.
3. Stacked bar chart showing the distribution of ECOG performance status (0, 1, and 2) across all treatment arms, to verify baseline functional status balance.
4. Grouped bar chart comparing the percentage of patients with KRAS mutation status (kras_g12c) for each treatment arm.
5. Box plot of baseline CA 19-9 tumor marker levels by treatment arm, to assess the distribution and balance of this key prognostic biomarker.
6. Kaplan-Meier plot for Overall Survival (OS), comparing all five treatment arms on a single graph.
7. Kaplan-Meier plot for Progression-Free Survival (PFS), comparing all five treatment arms on a single graph.
8. Bar chart displaying the median Overall Survival (in months) for each arm, with error bars representing the 95% confidence interval.

9. Bar chart displaying the median Progression-Free Survival (in months) for each arm, with error bars representing the 95% confidence interval.
10. Bar chart of the 12-month Overall Survival rate for each treatment arm, to visually represent this key timepoint metric.
11. Kaplan-Meier plot for Time to First Grade ≥ 3 Adverse Event, comparing all treatment arms to visualize safety profiles over time.
12. Bar chart showing the overall incidence rate (%) of patients experiencing a Grade ≥ 3 Adverse Event within 24 months, for each treatment arm.
13. Forest plot or bar chart visualizing the Overall Survival Hazard Ratios (and 95% CIs) for each experimental arm relative to the control arm.
14. Forest plot or bar chart visualizing the Progression-Free Survival Hazard Ratios (and 95% CIs) for each experimental arm relative to the control arm.
15. Scatter plot of Time to Progression vs. Overall Survival for all patients, colored by treatment arm, to show the correlation between endpoints.
16. Violin plot showing the distribution of Overall Survival time for each treatment arm, to compare the full range and density of survival outcomes.
17. Kaplan-Meier plot for Overall Survival stratified by ECOG status (ECOG 0 vs. ECOG 1-2) for the most effective arm (Arm A) versus the control arm (Arm E).
18. Kaplan-Meier plot for Overall Survival stratified by KRAS mutation status (kras_g12c), comparing outcomes within the most effective arm (Arm A).
19. Kaplan-Meier plot for Overall Survival stratified by gBRCA mutation status, comparing outcomes for all arms combined.
20. Scatter plot of baseline CA 19-9 levels versus Overall Survival time for all patients, colored by treatment arm to identify prognostic value.
21. Bar chart comparing median Overall Survival between younger (<65 years) and older (≥ 65 years) patient subgroups, faceted by treatment arm.
22. Heatmap showing the Pearson correlation matrix between continuous variables: age, CA 19-9, time to progression, time to death, and time to first G3 AE.
23. A risk-benefit bubble chart where the X-axis is median PFS, Y-axis is median OS, and the bubble size represents the Grade ≥ 3 AE rate for each arm.
24. Swarm plot showing individual patient survival times for each arm, providing a granular view of the outcome distribution and censoring.
25. Cumulative incidence plot for Grade ≥ 3 AEs, with death as a competing risk, comparing the triplet arm (Arm A) to the control arm (Arm E).
26. Box plots comparing Overall Survival across different patient archetype groups to explore this novel variable.
27. Scatter plot of Time to First Grade ≥ 3 AE versus Overall Survival time, colored by treatment arm, to investigate the relationship between early toxicity and efficacy.
28. Waterfall plot of individual patient survival times in the most effective arm (Arm A), ordered from shortest to longest survival.
29. Grouped bar chart comparing median Progression-Free Survival in patients with high vs. low baseline CA 19-9 (split by the median), for each arm.
30. Stacked bar chart showing the cause of PFS events (progression vs. death) for each treatment arm, if such data can be inferred from the time-to-event variables.

Output:

Thanks for uploading the file. Just to confirm before I start generating all 30 plots, would you like each visualization saved as a separate PNG file in a ZIP folder for download? Also, is there a preferred naming convention for the files or should I use short descriptive titles (e.g., '01_patient_counts.png')?

Input:

Use provided prompt.

Generation 39 (Formatted)

ChatGPT o3-pro Research

3088 words, 46 minutes 45.82 seconds

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The overlaid density plots illustrate that all treatment arms have very similar age distributions. Each arm's age curve peaks around the late 60s, with a range roughly from 40 to 80 years. There are no significant age profile differences between arms, suggesting that the randomization achieved a balanced age distribution across cohorts.

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This stacked bar chart indicates the distribution of ECOG performance status (0, 1, 2) in each arm. All arms show a similar breakdown: the majority of patients have ECOG 1, with smaller proportions of ECOG 0 and very few ECOG 2. The near-uniform gray shading across arms confirms that baseline functional status is well-balanced, with no arm having notably fitter or frailer patients.

4. KRAS G12C Mutation Prevalence by Arm

Each arm has about 5% of patients with the KRAS G12C mutation. The grouped bar chart shows virtually identical heights (all at 5.0%) for the percentage of KRAS-mutant patients in Arms A through E. This confirms that KRAS G12C status was evenly distributed by randomization, with no arm enriched or depleted for this mutation.

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The box plots display the distribution of baseline CA 19-9 tumor marker levels in each arm. Medians (green line) are all around 5,000–6,000 U/mL and the interquartile ranges overlap substantially among arms. While there is substantial variability within each arm (whiskers and spread extend from near 0 up to ~15,000+), the similarity of median values suggests the arms were comparable in baseline tumor burden as measured by CA 19-9.

6. Kaplan–Meier Overall Survival (OS) by Arm

The KM curves show clear separation between treatment arms for overall survival. Arm A (blue) has the highest survival probability at all time points, followed by Arm D (pink), indicating these regimens improved OS relative to control. Arm E (yellow, control) drops fastest – median OS ~6 months – whereas Arm A's median OS is ~8.8 months. By 24 months, ~15% of Arm A patients are alive versus only ~6% in Arm E, highlighting a survival benefit with the experimental triplet regimen.

7. Kaplan–Meier Progression-Free Survival (PFS) by Arm

PFS curves for all arms decline steeply, reflecting the aggressive nature of metastatic PDAC. Arm A again shows the best outcome – its curve (blue) is slightly above the others, indicating delayed progression or death. The control Arm E (yellow) has the poorest PFS, with a median around 2.1 months versus ~2.9 months in Arm A. Although differences between arms are somewhat modest on the PFS scale (all medians under 3 months), the ordering of curves ($A > D > C \approx B > E$) aligns with their OS rankings.

8. Median Overall Survival by Arm (95% CI)

This bar chart compares median OS for each arm, with error bars denoting 95% confidence intervals. Arm A's median OS is about 8.8 months (CI ≈ 8.7 – 9.0), the longest among arms. Arm D follows at ~8.1 months, while Arms C and B have intermediate medians (~7.1 and 6.7 months, respectively). The control Arm E has the shortest median OS at ~6.1 months. Error bars are very narrow (reflecting the large sample size), and there is no overlap between Arm A and Arm E, confirming a statistically significant OS benefit for Arm A over control.

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Median PFS is very short for all arms, but shows the same rank order as OS. Arm A achieves the longest median PFS (~2.93 months), narrowly edging Arm D (~2.71 months). Arm E's median PFS is ~2.08 months, the shortest. The differences in median PFS between arms are on the order of only a few weeks. The 95% confidence intervals (error bars) for these medians are extremely tight (on the order of ± 0.05 months) due to the large sample size, indicating the small differences are still statistically significant.

10. 12-Month Overall Survival Rates by Arm

The one-year OS rates differ markedly by arm. Approximately 39% of Arm A patients are alive at 12 months, compared to only 25% in the control Arm E. Arms D and C also show higher 12-month survival (35.5% and 30.9%, respectively) than control. Arm B's 12-month survival (~29%) is slightly better than Arm E's, but still lagging behind the novel combinations. This visual highlights Arm A's substantial improvement in one-year survival (a key milestone often cited in clinical trials) relative to standard-of-care.

11. Time to First Grade ≥ 3 Adverse Event (AE) – KM by Arm

The KM curves for time to first Grade ≥ 3 AE indicate that Arm A (blue) has the highest risk of early high-grade toxicity. Its curve drops fastest – for example, at 6 months only ~40% of Arm A patients remain free of a Grade 3–5 AE, compared to ~60% in Arm E (yellow). By 24 months, only ~10% of Arm A patients avoided any severe AE, versus ~24% in Arm E. All experimental arms show faster declines than control, indicating higher rates of severe adverse events with the combination therapies (particularly the triplet in Arm A).

12. Grade ≥ 3 AE Incidence by Arm (Within 24 Months)

This bar chart shows the overall incidence of Grade ≥ 3 adverse events by 24 months for each arm. The control Arm E has the lowest rate (~76% of patients experienced \geq Grade 3 AEs), whereas Arm A has the highest (~94%). Arms B, C, D have intermediate rates (around 81–88%). The gradient corresponds to regimen intensity: the more complex experimental arms (especially the triplet in Arm A) caused severe toxicities in a larger proportion of patients. These differences underscore a trade-off between efficacy and toxicity.

13. Overall Survival Hazard Ratios vs Control (Arm E)

The forest-style bar chart illustrates the hazard ratios (HRs) for OS for each experimental arm relative to control (Arm E = 1.0). Arm A achieved an OS HR of ~0.68 (95% CI ~0.66–0.69), indicating a ~32% reduction in risk of death versus standard therapy. Arm D's HR ~0.75 is also significantly <1.0. Arms C and B show more modest benefits (HR ~0.85 and 0.89, respectively). All confidence intervals lie entirely below 1, reinforcing that each experimental regimen improved OS relative to control, with Arm A being the most effective.

14. Progression-Free Survival Hazard Ratios vs Control

The PFS hazard ratios follow a similar pattern to OS, though closer to unity. Arm A's PFS HR is ~0.69 (meaning about a 31% reduction in risk of progression/death compared to control). Arm D's HR ~0.76 also shows a benefit. Arm C's HR ~0.82 and Arm B's ~0.94 suggest smaller PFS improvements – indeed Arm B's PFS HR (0.94) indicates only a marginal effect on delaying progression. The tighter clustering of PFS HRs near 1.0 reflects that while these novel therapies modestly prolonged time to progression, their major impact was more pronounced in overall survival outcomes.

15. Time to Progression vs Overall Survival (Scatter)

This scatter plot (all patients) illustrates the relationship between PFS and OS on a per-patient basis. Each point represents one patient's time to progression (x-axis) and overall survival (y-axis), color-coded by treatment arm. Most points lie below the diagonal line ($y = x$), meaning OS exceeds PFS – patients generally survive some time after progression. There is a positive correlation between PFS and OS, though not perfect. Notably, a cluster of points near

the $x = y$ line at low values indicates many patients progressed and died early (common in PDAC), while those with longer OS tend to have had later progression events.

16. Overall Survival Distributions by Treatment Arm (Violin Plot)

Violin plots provide a fuller picture of OS time distribution for each arm. The shape and width of each violin indicate the density of patients at different survival times. Arm A and Arm D not only have higher median OS (white dot) but also show longer upper tails – more patients achieving long survival (approaching the 24 month mark) compared to other arms. In contrast, Arm E's distribution skews lower, with a majority of its density under ~6 months. All arms have a wide spread (many patients unfortunately die very early, as seen by the violin stretching down to <3 months in every arm).

17. OS in Arm A vs Arm E, Stratified by ECOG

Kaplan–Meier curves for Arm A (blue) and Arm E (pink) are plotted separately for ECOG 0 and ECOG 1–2 patients. As expected, in both arms the ECOG 0 subgroup (solid lines) has better survival than the ECOG 1–2 subgroup (dashed lines). Arm A's ECOG 0 patients have the best outcomes, maintaining ~50% survival at 12 months, whereas Arm E's ECOG 1–2 patients fare worst (median OS only ~5 months). Importantly, Arm A's survival advantage over Arm E persists within each performance status stratum – even patients with poorer ECOG (1–2) live longer with Arm A than similar ECOG patients on control.

18. OS in Arm A by KRAS Mutation Status

These OS curves (Arm A only) compare KRAS G12C mutant vs wild-type patients. The blue and pink curves nearly overlap, indicating no meaningful survival difference between KRAS-mutant and KRAS wild-type patients within Arm A. The median OS and 2-year survival appear equivalent for both subgroups. This suggests that the efficacy of the Arm A triplet regimen is not markedly influenced by KRAS G12C mutation status – at least in terms of overall survival, KRAS was not a clear prognostic or predictive factor in this trial cohort.

19. OS by Germline BRCA Mutation Status (All Arms Combined)

When pooling all arms, overall survival was very similar for patients with vs. without a germline BRCA mutation. The orange curve (gBRCA wild-type) and yellow curve (gBRCA mutant) are virtually indistinguishable. Both subgroups have median OS around 7 months and nearly identical survival trajectories. Thus, in this trial population, germline BRCA status did not have a noticeable impact on survival outcomes – possibly due to the lack of PARP inhibitor use or other BRCA-targeted strategies in the treatment regimens.

20. Baseline CA 19-9 vs Overall Survival (Scatter)

This scatter plot explores the prognostic value of baseline CA 19-9 tumor marker. The x-axis is on a log scale for CA 19-9 levels, and the y-axis is OS in months. The dense cloud of points (color-coded by arm) indicates a weak negative correlation: patients with very high CA 19-9 (far right) tend to cluster towards lower survival times, but the trend is not strong. Many patients with low or moderate CA 19-9 also died early. The correlation matrix confirms only a near-zero correlation ($r \sim -0.01$) between CA 19-9 and OS, suggesting baseline CA 19-9 by itself was not a strong predictor of survival in this trial.

21. Median OS by Age Group (<65 vs ≥65) in Each Arm

Grouped bars compare median OS for younger (<65) vs older (≥65) patients in each arm. The blue and green bars within each arm are almost equal height, indicating minimal age effect on survival under these treatments. For instance, in Arm A median OS was ~8.81 months for <65 vs 8.82 months for ≥65 – essentially identical. Similarly minor differences (≤0.2 months) are seen in other arms. These results imply that the therapies' efficacy did not differ by age subgroup (and any slight numerical differences are likely not clinically meaningful).

22. Pearson Correlation Matrix (Continuous Variables)

This heatmap shows Pearson correlation coefficients among key continuous baseline and outcome variables. All off-diagonal values are near 0.00, indicating no strong linear relationships. Notably, age has essentially zero correlation with CA 19-9 or survival times, and CA 19-9 has virtually no correlation with time to progression or OS (each $r \sim 0.00$). Even time to progression vs time to death only correlates at $r \approx 0.02$, reflecting the substantial influence of post-progression survival. The absence of significant correlations suggests these variables were largely independent in this dataset.

23. Risk–Benefit Bubble Chart (Median OS vs PFS)

In this bubble chart, each arm is plotted by its median PFS (x-axis) and median OS (y-axis), with bubble size proportional to the arm's Grade ≥3 AE rate. The experimental arms (A–D) all lie to the upper right of control (E), signifying better efficacy (longer medians). Arm A (blue bubble) is furthest up and right, achieving the highest OS (~8.8 mo) and PFS (~2.9 mo) but also has the largest bubble (reflecting a ~94% severe AE rate). Arm E (yellow) is bottom-left with the smallest bubble (poorest survival but fewer toxicities). The positions illustrate the trade-off: arms with greater efficacy (A, D) also incurred more toxicity, whereas the control had lower toxicity but worse survival.

24. Individual Patient OS Times by Arm (Swarm Plot)

This swarm-like plot shows every patient's overall survival time, by arm. Each blue dot represents a patient death, jittered horizontally within each arm category. Red "x" symbols along the top indicate censored patients (those still alive or lost to follow-up at 24 months). We observe a dense block of blue points near the bottom of each column – many patients died very early regardless of arm. However, Arm A and D columns have a thicker spread of blue dots extending higher (more patients achieving long survival), whereas Arm E's blue dots are mostly packed near the bottom. The red markers at 24 months are somewhat more frequent in Arm A and D, corresponding to their higher tail of survivors.

25. Cumulative Incidence of Grade ≥3 AEs (Arm A vs Arm E)

This plot depicts the cumulative incidence of experiencing a Grade ≥3 adverse event over time, treating death as a competing risk (so curves level off below 100%). By 6 months, ~40% of Arm A patients and ~25% of Arm E patients had suffered a severe AE. The incidence curves rise over time and eventually plateau: by 24 months, about 60% of Arm A patients had a Grade ≥3 AE before either experiencing one or dying, compared to ~30% in Arm E. Thus, even accounting for patients who die early (and never have an AE), Arm A clearly inflicted significantly more toxicity over the course of the trial than the control regimen.

26. Overall Survival by Patient Archetype

Box plots stratified by patient “archetype” show that baseline archetype groups had broadly similar OS outcomes. The medians (green lines) for ARCH-01 through ARCH-07 range roughly 6–8 months, and their box heights and whiskers overlap substantially. There is no archetype that stands out as having dramatically better or worse survival. This suggests that the novel “archetype” variable was not strongly prognostic for OS in this study, or any effect was subtle relative to the overall variability.

27. Time to First G3 AE vs Overall Survival (Scatter)

This scatter plot examines whether early toxicity is associated with survival. The horizontal axis is time to first Grade ≥ 3 AE and the vertical axis is OS, with each point colored by arm. Notably, there are many points along the bottom-right region, i.e. patients who died (low OS) without ever experiencing a Grade 3 AE (high AE time – often set to 24 months). Conversely, we see some points in the top-left quadrant – patients who had an early severe AE but nonetheless survived a long time. Overall, the cloud is quite diffuse, and the correlation is near zero (the correlation matrix gave $r \approx -0.02$ for time to AE vs OS). Thus, experiencing an early Grade ≥ 3 toxicity does not show a clear relationship with shorter or longer survival in this dataset.

28. Arm A Survival Times (Waterfall Plot)

The waterfall plot orders each Arm A patient’s OS from shortest to longest. It creates a smooth blue curve rising from 0 up to ~24 months (the longest survivors). This illustrates the distribution of outcomes: about half the patients are to the left of the red dashed median line (~8.8 months) and half to the right. The steep rise in the rightmost segment of the curve indicates a minority of patients achieved much longer survival (the top ~10–15% lived beyond 15 months). Meanwhile, the flat portion near the origin shows a substantial fraction with very short survival. Overall, Arm A’s curve highlights both the life-prolonging impact of the triplet and the persistent reality that many PDAC patients still succumb early despite aggressive therapy.

29. Median PFS by CA 19-9 Subgroup (High vs Low)

This grouped bar chart compares median PFS in patients with high vs low baseline CA 19-9 (split at the overall median) for each arm. The blue (“Low CA 19-9”) and green (“High CA 19-9”) bars are nearly identical within every arm. For example, in Arm E median PFS was ~2.11 months for low CA 19-9 vs 2.06 months for high CA 19-9 – a negligible difference. This pattern holds for all arms (differences ≤ 0.05 months). Thus, baseline CA 19-9 level (whether above or below median) did not meaningfully affect progression-free survival in any treatment group.

30. Cause of PFS Events by Treatment Arm (Progression vs Death)

Each bar is divided into two segments representing how patients’ PFS events occurred: disease progression (green) or death before progression (orange). Across arms ~65–67% of patients progressed first, while ~33–35% died without documented progression. Arm C (orange segment ~34.9%) had a slightly higher fraction of death-driven PFS events, whereas Arm B had slightly fewer (orange ~32.7%). These small differences aside, all arms show that roughly one-third of PFS events were deaths, underscoring that a significant subset of patients died early without radiologic progression. The similar progression vs death splits across arms also indicate that no regimen dramatically altered the mode of PFS event – the improvements in PFS were primarily due to delaying both progression and death events proportionally.

Generation 39 (Plain Text)

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Violin plots provide a fuller picture of OS time distribution for each arm. The shape and width of each violin indicate the density of patients at different survival times. Arm A and Arm D not only have higher median OS (white dot) but also show longer upper tails – more patients achieving long survival (approaching the 24 month mark) compared to other arms. In contrast, Arm E's distribution skews lower, with a majority of its density under ~ 6 months. All arms have a wide spread (many patients unfortunately die very early, as seen by the violin stretching down to < 3 months in every arm).

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Kaplan–Meier curves for Arm A (blue) and Arm E (pink) are plotted separately for ECOG 0 and ECOG 1–2 patients. As expected, in both arms the ECOG 0 subgroup (solid lines) has better survival than the ECOG 1–2 subgroup (dashed lines). Arm A's ECOG 0 patients have the best outcomes, maintaining $\sim 50\%$ survival at 12 months, whereas Arm E's ECOG 1–2 patients fare worst (median OS only ~ 5 months). Importantly, Arm A's survival advantage over Arm E persists within each performance status stratum – even patients with poorer ECOG (1–2) live longer with Arm A than similar ECOG patients on control.

18. OS in Arm A by KRAS Mutation Status

 These OS curves (Arm A only) compare KRAS G12C mutant vs wild-type patients. The blue and pink curves nearly overlap, indicating no meaningful survival difference between KRAS-mutant and KRAS wild-type patients within Arm A. The median OS and 2-year survival appear equivalent for both subgroups. This suggests that the efficacy of the Arm A triplet regimen is not markedly influenced by KRAS G12C mutation status – at least in terms of overall survival, KRAS was not a clear prognostic or predictive factor in this trial cohort.

19. OS by Germline BRCA Mutation Status (All Arms Combined)

 When pooling all arms, overall survival was very similar for patients with vs. without a germline BRCA mutation. The orange curve (gBRCA wild-type) and yellow curve (gBRCA mutant) are virtually indistinguishable. Both subgroups have median OS around 7 months and nearly identical survival trajectories. Thus, in this trial population, germline BRCA status did not have a noticeable impact on survival outcomes – possibly due to the lack of PARP inhibitor use or other BRCA-targeted strategies in the treatment regimens.

20. Baseline CA 19-9 vs Overall Survival (Scatter)

 This scatter plot explores the prognostic value of baseline CA 19-9 tumor marker. The x-axis is on a log scale for CA 19-9 levels, and the y-axis is OS in months. The dense cloud of points (color-coded by arm) indicates a weak negative correlation: patients with very high CA 19-9 (far right) tend to cluster towards lower survival times, but the trend is not strong. Many patients with low or moderate CA 19-9 also died early. The correlation matrix confirms only a near-zero correlation ($r \sim -0.01$) between CA 19-9 and OS, suggesting baseline CA 19-9 by itself was not a strong predictor of survival in this trial.

21. Median OS by Age Group (<65 vs ≥65) in Each Arm

 Grouped bars compare median OS for younger (<65) vs older (≥65) patients in each arm. The blue and green bars within each arm are almost equal height, indicating minimal age effect on survival under these treatments. For instance, in Arm A median OS was ~ 8.81 months for <65 vs 8.82 months for ≥65 – essentially identical. Similarly minor differences (≤ 0.2 months) are seen in other arms. These results imply that the therapies' efficacy did not differ by age subgroup (and any slight numerical differences are likely not clinically meaningful).

22. Pearson Correlation Matrix (Continuous Variables)

 This heatmap shows Pearson correlation coefficients among key continuous baseline and outcome variables. All off-diagonal values are near 0.00, indicating no strong linear relationships. Notably, age has essentially zero correlation with CA 19-9 or survival times, and CA 19-9 has virtually no correlation with time to progression or OS (each $r \sim 0.00$). Even time to progression vs time to death only correlates at $r \approx 0.02$, reflecting the substantial influence of

post-progression survival. The absence of significant correlations suggests these variables were largely independent in this dataset.

23. Risk–Benefit Bubble Chart (Median OS vs PFS)

 In this bubble chart, each arm is plotted by its median PFS (x-axis) and median OS (y-axis), with bubble size proportional to the arm’s Grade ≥ 3 AE rate. The experimental arms (A–D) all lie to the upper right of control (E), signifying better efficacy (longer medians). Arm A (blue bubble) is furthest up and right, achieving the highest OS (~ 8.8 mo) and PFS (~ 2.9 mo) but also has the largest bubble (reflecting a $\sim 94\%$ severe AE rate). Arm E (yellow) is bottom-left with the smallest bubble (poorest survival but fewer toxicities). The positions illustrate the trade-off: arms with greater efficacy (A, D) also incurred more toxicity, whereas the control had lower toxicity but worse survival.

24. Individual Patient OS Times by Arm (Swarm Plot)

 This swarm-like plot shows every patient’s overall survival time, by arm. Each blue dot represents a patient death, jittered horizontally within each arm category. Red “x” symbols along the top indicate censored patients (those still alive or lost to follow-up at 24 months). We observe a dense block of blue points near the bottom of each column – many patients died very early regardless of arm. However, Arm A and D columns have a thicker spread of blue dots extending higher (more patients achieving long survival), whereas Arm E’s blue dots are mostly packed near the bottom. The red markers at 24 months are somewhat more frequent in Arm A and D, corresponding to their higher tail of survivors.

25. Cumulative Incidence of Grade ≥ 3 AEs (Arm A vs Arm E)

 This plot depicts the cumulative incidence of experiencing a Grade ≥ 3 adverse event over time, treating death as a competing risk (so curves level off below 100%). By 6 months, $\sim 40\%$ of Arm A patients and $\sim 25\%$ of Arm E patients had suffered a severe AE. The incidence curves rise over time and eventually plateau: by 24 months, about 60% of Arm A patients had a Grade ≥ 3 AE before either experiencing one or dying, compared to $\sim 30\%$ in Arm E. Thus, even accounting for patients who die early (and never have an AE), Arm A clearly inflicted significantly more toxicity over the course of the trial than the control regimen.

26. Overall Survival by Patient Archetype

 Box plots stratified by patient “archetype” show that baseline archetype groups had broadly similar OS outcomes. The medians (green lines) for ARCH-01 through ARCH-07 range roughly 6–8 months, and their box heights and whiskers overlap substantially. There is no archetype that stands out as having dramatically better or worse survival. This suggests that the novel “archetype” variable was not strongly prognostic for OS in this study, or any effect was subtle relative to the overall variability.

27. Time to First G3 AE vs Overall Survival (Scatter)

This scatter plot examines whether early toxicity is associated with survival. The horizontal axis is time to first Grade ≥ 3 AE and the vertical axis is OS, with each point colored by arm. Notably, there are many points along the bottom-right region, i.e. patients who died (low OS) without ever experiencing a Grade 3 AE (high AE time – often set to 24 months). Conversely, we see some points in the top-left quadrant – patients who had an early severe AE but nonetheless survived a long time. Overall, the cloud is quite diffuse, and the correlation is near zero (the correlation matrix gave $r \approx -0.02$ for time to AE vs OS). Thus, experiencing an early Grade ≥ 3 toxicity does not show a clear relationship with shorter or longer survival in this dataset.

28. Arm A Survival Times (Waterfall Plot)

The waterfall plot orders each Arm A patient's OS from shortest to longest. It creates a smooth blue curve rising from 0 up to ~ 24 months (the longest survivors). This illustrates the distribution of outcomes: about half the patients are to the left of the red dashed median line (~ 8.8 months) and half to the right. The steep rise in the rightmost segment of the curve indicates a minority of patients achieved much longer survival (the top $\sim 10\text{--}15\%$ lived beyond 15 months). Meanwhile, the flat portion near the origin shows a substantial fraction with very short survival. Overall, Arm A's curve highlights both the life-prolonging impact of the triplet and the persistent reality that many PDAC patients still succumb early despite aggressive therapy.

29. Median PFS by CA 19-9 Subgroup (High vs Low)

This grouped bar chart compares median PFS in patients with high vs low baseline CA 19-9 (split at the overall median) for each arm. The blue ("Low CA 19-9") and green ("High CA 19-9") bars are nearly identical within every arm. For example, in Arm E median PFS was ~ 2.11 months for low CA 19-9 vs 2.06 months for high CA 19-9 – a negligible difference. This pattern holds for all arms (differences ≤ 0.05 months). Thus, baseline CA 19-9 level (whether above or below median) did not meaningfully affect progression-free survival in any treatment group.

30. Cause of PFS Events by Treatment Arm (Progression vs Death)

Each bar is divided into two segments representing how patients' PFS events occurred: disease progression (green) or death before progression (orange). Across arms $\sim 65\text{--}67\%$ of patients progressed first, while $\sim 33\text{--}35\%$ died without documented progression. Arm C (orange segment $\sim 34.9\%$) had a slightly higher fraction of death-driven PFS events, whereas Arm B had slightly fewer (orange $\sim 32.7\%$). These small differences aside, all arms show that roughly one-third of PFS events were deaths, underscoring that a significant subset of patients died early without radiologic progression. The similar progression vs death splits across arms also indicate that no regimen dramatically altered the mode of PFS event – the improvements in PFS were primarily due to delaying both progression and death events proportionally.

Research Summary Generation 39: 2780 Words

Visualizations for PDAC Phase III Clinical Trial Analysis

ChatGPT

OK, let me see if I've got this: pulling data, setting up visuals, and detailing analysis steps for the PDAC cancer trial log file. Each visualization will be crafted meticulously.

Analyzed with python

ChatGPT

I'm piecing together the event times and exploring how "time_to_progression_or_death" might relate to progression or death and whether censored events need consideration.

Analyzed with python

ChatGPT

I'm mapping out how to analyze progression-free survival (PFS) by comparing time_to_progression_or_death and time_to_death to pinpoint the earliest event. I'm thinking through censoring, especially if progression or death hasn't happened by the 24-month mark.

Analyzed with python

ChatGPT

I'm tasked with creating 30 various plots for a Ph III PDAC trial, ensuring each image is clearly labeled and embedded with a concise caption.

Analyzed with python

ChatGPT

Considering pip installing lifelines or scikit-survival, or manually plotting with matplotlib.

Analyzed with python

ChatGPT

I'm thinking about Kaplan-Meier curves and hazard ratios for survival analysis. Concurrently, I'm pondering methods to approximate median values and confidence intervals for 100k samples.

Examining bootstrap and normal approximation for median survival CI. Considering Poisson variance for hazard ratio CI. Confirming balanced event counts and median OS estimation for each arm.

Analyzed with python

ChatGPT

I'm working through data on overall survival (OS) and progression-free survival (PFS) events, considering early death and informal progression events. Progression or lack thereof influences PFS event categorization.

I'm mapping out the use of Python and Matplotlib/Seaborn to create clear, consistently styled plots. This involves selecting appropriate visualization types based on data characteristics, such as bar charts for KRAS mutation percentages and box plots for CA19-9 baseline values.

Analyzed with python

ChatGPT

I'm noting the distribution of survival times, suggesting a robust approach to handle frequent outliers in boxplots and considering linear scales or logarithmic transformations for better visualization.

I'm mapping out the interpretation of the 12-month OS rate, distinguishing between those who survive to 12 months and those who do not, while noting the complexities of time and event simulation.

Analyzed with python

ChatGPT

I'm mapping out the survival rate at 12 months using Kaplan-Meier, adjusting for events at exactly 12 months. For adverse events, I'm considering those censored post-12 months as alive at 12, calculating the fraction of patients alive beyond 12 months. This reflects a practical survival metric.

Analyzed with python

ChatGPT

I'm evaluating hazard ratios for arms A to E, noting their survival chances compared to Arm E. The range (0.68-0.89) indicates significant relative risk.

I'm working through calculating progression-free survival (PFS) times by taking the minimum of progression or death time for each patient, carefully handling cases where both are 24.

Analyzed with python

ChatGPT

I'm focusing on progression-free survival (PFS) rates across different arms, noting how Arm A leads in lower hazard. Progression events offer key insights for comparison.

Analyzed with python

ChatGPT

I'm mapping out scatter plots and violin plots to illustrate survival trends and correlations within patient subgroups, ensuring clarity and insightful comparisons.

Analyzed with python

ChatGPT

OK, let's think this through: about half the people in each age group, with the younger group possibly having fewer deaths. Now, I'm considering using direct median times or Kaplan-Meier to ensure consistency.

Analyzed with python

ChatGPT

I'm noting a risk-benefit bubble chart with x-axis median PFS, y-axis median OS, and bubble size as Grade ≥ 3 AE rate per arm.

Analyzed with python

ChatGPT

Considering bubble sizes for G3 AE rates. Trying constants to highlight differences without overlapping clusters.

Analyzed with python

ChatGPT

I'm noting the medians for categories A to E, with times likely in months. The data suggests the practice duration is relatively short, possibly indicating PDAC.

Analyzed with python

ChatGPT

I'm evaluating a combined view of survival and adverse effects for each treatment arm, selecting up to 50 random values to ensure clear data representation.

Analyzed with python

ChatGPT

Using a waterfall plot to visualize survival trends in Arm A. Considering patient OD times, adjusting parameters for clarity.

Analyzed with python

ChatGPT

I'm segmenting the analysis by grouping the data by treatment arm and CA group to compute median PFS times for each specific subgroup, ensuring a clear and detailed division for accurate comparison.

Analyzed with python

ChatGPT

Mapping out minute variations in PFS events, focusing on progression and death causes while assessing the influence of CA19-9 levels.

Considering if simultaneous progression and death should be categorized as either progression or death for overall event type. Leaning towards categorizing as death cause.

Analyzed with python

Analyzed with python

Analyzed with python

ChatGPT

I'm assembling each figure with a clear title, image, and a concise explanation. Avoiding clutter is key, so I'll keep all descriptions within 3-5 sentences.

Analyzed with python

Analyzed with python

ChatGPT

OK, let's think through the numbers. Each percentage share is exactly 5%, signifying a well-balanced distribution.

Analyzed with python

ChatGPT

Interestingly enough, OS K-M plots show Arm A and D with better survival than control, while Arm E falls behind. Will append median OS bars and compute 200 bootstrap replications to refine error bars.

Analyzed with python

ChatGPT

OK, let's see. The narrow confidence intervals for A and E, both around 0.23, suggest high precision in their estimates. This precision underscores their reliability in bar #8.

Analyzed with python

ChatGPT

I'm focusing on setting a moderate DPI, like 150 or 200, to ensure image clarity without large file sizes. Also, considering fonts and styles for a unified, colorblind-friendly aesthetic.

I'm assembling a bar chart showing patient counts across treatment arms A-E. Each arm has 20,000 patients, adding data labels for clarity.

Analyzed with python

Read from S37.TRL.14.P30.LOG.csv

ChatGPT

I noticed the browser opened the CSV file instead of the image. I plan to find out how to display the saved images, since no images appeared in the search results.

Searched for PNG files

ChatGPT

I'm evaluating whether listing is necessary.

I'm exploring how to show an image in Python without using `plt.show()` or saving to a file. Reading it as a binary file or using `IPython.display.Image` are considered alternatives.

Analyzed with python

ChatGPT

Interestingly, images in Python output are organized by file paths. Each image is sequentially numbered, with the initial image labeled [32+embed_image].

Analyzed with python

ChatGPT

Hmm, I'm thinking about the xlim to 18-110 to capture all age ranges. Hustling to see if randomization affects age differences across treatment arms.

Analyzed with python

ChatGPT

I'm thinking about whether the loop with `sns.kdeplot` caused the issue and if the `display(Image())` ensures image output.

I'm analyzing the image sequence to pinpoint the next number, likely [34] or [35].

I'm curious if Python's display function silently failed and suggestion to break the code for better monitoring.

Searched for plot02_age_density.png

ChatGPT

I'm experimenting with various methods like using IPython's display, `plt.show()`, or reading the saved file as bytes.

Analyzed with python

Analyzed with python

ChatGPT

I'm thinking about adjusting the Python code to ensure each image is shown via a separate block, which will provide distinct indices for accurate referencing.

Analyzed with python

ChatGPT

I'm noting that directly referencing `Image(path)` at the end of each code block automatically produces output without the need for explicit display calls, ensuring figures are properly saved and closed without conflicts.

Analyzed with python

ChatGPT

Ensuring `Image()` as the last statement may resolve visibility issues.

Analyzed with python

ChatGPT

I'm thinking through potential bugs in the code, including execution failures and drawing inconsistencies.

Analyzed with python

ChatGPT

I'm thinking through why the UI isn't showing images, suspecting it isn't interactive or might be grouping them. Progressing to explore these aspects.

I'm thinking it's best to generate each image in a separate cell to ensure it displays properly. Starting with [35], I'm working through the next step with [36] or [37].

It seems the file might not exist since there's no output, even though it was saved.

Analyzed with python

ChatGPT

I'm piecing together why the file didn't save. Considering blocks, figure code, image call, execution failures, or incorrect file path as potential causes.

Analyzed with python

ChatGPT

I'm noting that the issue might be resolved, and the progress is being assessed.

Analyzed with python

ChatGPT

I'm checking if the code can save a file, considering path correctness and permissions, and exploring directory options. Progress is steady.

Analyzed with python

ChatGPT

I'm piecing together why the file isn't writing successfully, considering code execution, environment permissions, and saving mechanics. No errors suggest the code ran but didn't flush properly.

Analyzed with python

ChatGPT

I'm thinking through whether spaces or hidden encodings in the file path might cause an issue with saving the plot.

Analyzed with python

ChatGPT

I'm thinking the problem might lie in seaborn's KDE plotting, with large datasets or specific parameters potentially causing the issue. File path and environment settings are also key considerations.

Analyzed with python

ChatGPT

The `common_norm=False` parameter might not be suitable for older seaborn versions, potentially causing issues without errors.

Analyzed with python

ChatGPT

Considering `kdeplot` and `histplot`. Haven't ruled out a smaller data sample for `kdeplot`.

Analyzed with python

Analyzed with python

ChatGPT

I'm digging into memory or timeouts due to quick returns or empty plots despite plenty of data points.

Analyzed with python

Analyzed with python

ChatGPT

Seaborn visualizations might not be rendering as expected due to non-interactive settings or save call timing.

Analyzed with python

ChatGPT

I'm considering if the issue with `test_kde2` is due to a problem with the fill or alpha settings, or if it's just slower.

Analyzed with python

ChatGPT

I'm working on letting seaborn KDE plot handle it, but also considering manual labels. Let's see which approach makes the most sense.

Analyzed with python

ChatGPT

I'm considering KDE for each arm, potentially using numpy histograms or scipy's `gaussian_kde` for density computation and smoothing.

Analyzed with python

ChatGPT

I'm noting the file's jagged edges yet acceptable form.

Analyzed with python

ChatGPT

I'm pulling together counts of ECOG levels for each arm and charting them to show progression. Tricky color choices for clear distinction!

Analyzed with python

ChatGPT

I'm integrating a grouped bar chart to compare KRAS mutation percentages across study arms, balancing clarity and data presentation.

Analyzed with python

ChatGPT

OK, let me see. Creating a bar chart with all bars at 5% highlights the even distribution of samples. Adding a text label for clarity emphasizes the uniformity.

Analyzed with python

ChatGPT

I'm examining the baseline CA19-9 values across 52 arms using a box plot. Considering linear scale to better identify outliers and simplifying the visualization by excluding outliers.

Analyzed with python

ChatGPT

I'm working on Kaplan-Meier survival curves for different arms, tallying event times, and updating risk values to chart out survival outcomes.

I'm thinking through the color mapping for different arms and confirming the PFS event logic. Particularly, how to accurately count progression and death events to prevent double counting.

Analyzed with python

ChatGPT

Examining PFS curves, it appears Arm A has the most favorable results, while Arm E shows the least promising outcomes, with subtle but noticeable differences.

Analyzed with python

ChatGPT

I'm organizing individual bar charts for each arm, planning to use `plt.bar` with asymmetric error bars to clearly show the median and range of months.

Analyzed with python

ChatGPT

I reviewed the bar chart with left arrows and right arrows. The median progression-free survival (PFS) with 95% confidence intervals (CI) for each arm looks correct as shown in Figure 8.

Analyzed with python

Analyzed with python

ChatGPT

I'm evaluating small variations in a 12-month overall survival (OS) rate bar chart, concentrating on fractions surviving beyond 12 months.

Assessing 5% yield.

Analyzed with python

Analyzed with python

Analyzed with python

Analyzed with python

ChatGPT

I'm working through a 12-month organizational structure (OS) Analyzing metrics: Arm A at 39.3%, D at 35.5%, C at 30.9%, B at 29.0%, and E at 25.2%, using bar charts for clarity.

Analyzed with python

ChatGPT

Setting event flags for each patient's timeline, considering AE or death at 24 or earlier, and mapping actual times for accurate Kaplan-Meier plotting.

Analyzed with python

ChatGPT

I'm examining the K-M curve to determine the probability of no G3 AE, noting Arm A sees a sharper decline ending at around 0.1 by 24, while Arm E stabilizes at approximately 0.24.

Analyzed with python

ChatGPT

I'm gathering the percentages into a bar chart for a clear visual comparison.

I'm thinking through whether a bar or forest plot best displays hazard ratios. Opting for bars with HR and 95% CI values, excluding baseline E.

Analyzed with python

ChatGPT

I'm plotting PFS hazard ratios for treatments A-D with 95% confidence intervals, using colors like light green or 'tab:orange' for differentiation.

Analyzed with python

ChatGPT

I'm examining a scatter plot of time to progression versus overall survival, colored by treatment arm, with adjustments for data density and reference lines.

Analyzed with python

ChatGPT

I'm mapping out the use of a violin plot to show OS by arm, considering color palettes and handling data artifacts like the spike at 24.

Analyzed with python

ChatGPT

Mapping out survival curves for Arm A and Arm E, differentiating by ECOG status, and exploring color and line style distinctions for clear results.

Analyzed with python

ChatGPT

Mapping out KRAS mutations in Arm A, using distinct colors or styles for easy differentiation. Prioritizing clear labels for transparency.

Analyzed with python

ChatGPT

Treating all patients as a single group for K-M curves, separating by gBRCA status to check survival differences.

Analyzed with python

ChatGPT

I'm curious about the 5% mutation rate and its potential correlation with treatment outcomes for PDAC, particularly in the context of gBRCA mutations and platinum therapy.

Analyzed with python

ChatGPT

Considering log and linear scales for CA19-9 to observe trends, excluding zeros to prevent distortion. This approach refines the model's precision.

Analyzed with python

ChatGPT

OK, let me see. Points with lower CA19-9 appeared to survive longer, while many with low OS clustered across CA levels.

Analyzed with python

ChatGPT

I'm gathering insights on displaying median differences between younger and older groups for each arm using seaborn's barplot.

Analyzed with python

ChatGPT

I'm evaluating correlations and opting for a heatmap to visualize these relationships, carefully considering the data's structure and impact.

Analyzed with python

ChatGPT

I'm piecing together a bubble chart: median PFS and OS for each treatment arm, with bubble size indicating AE rates. Colors and labels will clarify distinctions, while a comprehensive caption will finalize the explanation.

Analyzed with python

ChatGPT

I'm cutting down on the scatter legend by pulling the arm labels. This refines the legend size, balancing clarity and simplicity.

Analyzed with python

ChatGPT

I'm working through jittering x positions to separate data points for each arm, using distinct colors for events and censored individuals. This approach ensures clear visualization of survival times.

Analyzed with python

ChatGPT

I'm working through the Fine-Gray method to adjust for death, ensuring a comprehensive view of cumulative incidence for adverse events in Arms A and E.

Analyzed with python

ChatGPT

OK, let me see. I'm noting a drop in cumulative incidence at 24 months due to mortality, skewing event rates. Box plots will compare overall survival across archetype groups, ensuring clarity and consistency.

Analyzed with python

ChatGPT

OK, let me see: I'm verifying the checkbox and setting `showfliers=False` for the box.

Analyzed with python

ChatGPT

OK, I'm thinking through the scatter plot: time to first G3 AE on x-axis, OS on y-axis. Points with no AE will be just under the diagonal, showing death before AE.

Analyzed with python

ChatGPT

Piecing together individual survival times in Arm A, I'm thinking about using vertical lines to show time from 0 for each patient, considering clarity and interpretation.

Analyzed with python

ChatGPT

OK, I'm charting median PFS by arm groups using `median_pfs_by_cagroup`, a Series multiindex, ensuring clear visualization.

Analyzed with python

ChatGPT

I'm brainstorming different color schemes and patterns, like blue vs. orange, for high and low CA19-9 levels. Wishing to minimize confusion and use intuitive icons.

Analyzed with python

ChatGPT

Considering actual counts for progression and death events, with a small top segment for censoring, for clarity.

Analyzed with python

ChatGPT

I'm evaluating color schemes for progression and death events. Progression could be teal (`#66c2a5`), and death might be orange (`#fc8d62`). This approach should effectively highlight the events and maintain aesthetic coherence.

Analyzed with python

ChatGPT

I'm assembling the final answer by adding headings and incorporating images within paragraphs. Each image is described with 3-5 sentences, highlighting key points and any noted differences.

Analyzed with python

Research completed in 43m · 1 sources

Citations Generation 39

All Sources

[S37.TRL....0.LOG.csv](#)