2025 Software Industry Salary

Analysis Report

Which Technologies Pay More? How Do Career Levels and Roles Affect Salaries?

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September 2, 2025

Key Findings:

- Experience and seniority drive salaries, with Senior (130.8 k TL) and Management (184.8 k TL) roles 137-237% above Junior (55.1 k TL).
- Males earn 15.4% more than females (99.4 vs. 86.1 k TL), highlighting pay inequity.
- Remote (101.2 k TL) and Hybrid (105.0 k TL) roles offer 28.8-33.6% premiums over Office (78.6 k TL).
- European (162.9 k TL) and American (156.0-173.6 k TL) firms pay 75.3-113% more than Turkish companies (92.9 k TL).
- Niche technologies like Rust (70.7% ROI) outperform mainstream tools like React.

Based on data from 2,969 software professionals collected August 20-21, 2025

Prepared by Hakkı Günal — Data sourced from Zafer Ayan's 2025 Salary Survey (LinkedIn, Medium) — September 2, 2025

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Abstract

This report analyzes data from Zafer Ayan's 2025 Software Industry Salary Survey, conducted on August 20-21, 2025, with 2,969 software professionals, to explore compensation trends, technology impacts, and career dynamics. Key findings reveal that experience and seniority drive salaries, with Senior (130.8 k TL) and Management (184.8 k TL) roles earning 137-237% more than Junior (55.1 k TL). A 15.4% gender pay gap exists (males: 99.4 k TL, females: 86.1 k TL). Remote (101.2 k TL) and Hybrid (105.0 k TL) work offer 28.8-33.6% premiums over Office roles (78.6 k TL). European and American companies pay 75.3-113% more than Turkish firms. Niche technologies like Rust (70.7% ROI) yield higher returns than mainstream tools like React.

1 Executive Summary

This report, based on Zafer Ayan's 2025 Software Industry Salary Survey (LinkedIn, Medium) conducted on August 20-21, 2025, with 2,969 professionals, analyzes compensation, technology, and career trends in the software industry. It aims to guide developers in career planning and employers in talent strategies.

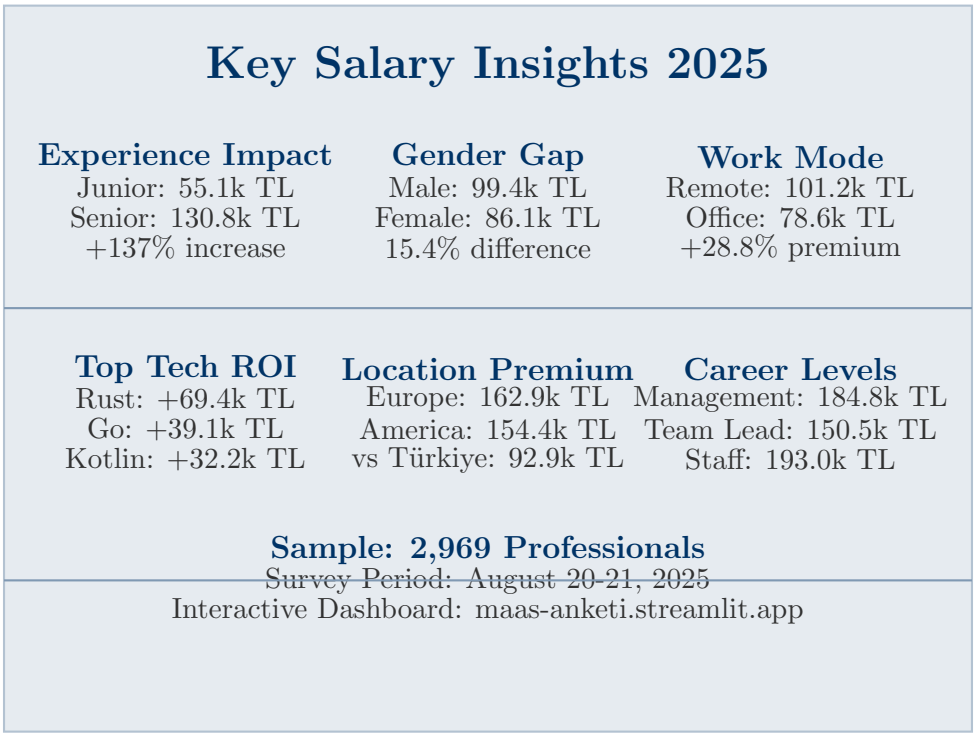

Figure 1: Executive Summary Infographic: Key Salary Insights and Trends

Key Findings:

- **Salary Drivers**: Experience (r = 0.623) and seniority (r = 0.474) drive salaries, with Senior (130.8 k TL) and Management (184.8 k TL) roles outpacing Junior (55.1 k TL) by 137.4-237.4%.
- **Gender Disparity**: Males earn 15.4% more than females (99.4 vs. 86.1 k TL, p = 0.00005).

- **Technology Impact**: Niche languages like Rust (70.7% ROI) and Go (r = 0.171) offer higher premiums than React (r = -0.028).
- **Work Modes**: Remote (101.2 k TL) and Hybrid (105.0 k TL) roles yield 28.8-33.6% more than Office (78.6 k TL).
- **Geographical Advantage**: European (162.9 k TL) and American (156.0-173.6 k TL) firms pay 75.3-113% more than Turkish companies (92.9 k TL).
- **Employment Types**: Full-time (99.0 k TL) earns 130.2% more than Part-time (43.0 k TL); Self-employed (123.4 k TL) earns 24.6% more than Full-time.

Interactive dashboard: maas-anketi.streamlit.app

2 Methodology

2.1 Data Collection

The survey data was collected by Zafer Ayan as part of his 2025 Software Industry Salary Survey, conducted online between August 20-21, 2025, targeting software professionals across various career levels and specializations (LinkedIn, Medium). The questionnaire covered demographic information, salary details, technology stack, work arrangements, and company characteristics. The raw data, including Google Sheets and analytics, were accessed from Ayan's shared resources (Google Sheets, Analytics).

Data Collection Limitations:

- **Time Constraint:** The survey was conducted over only 2 days (August 20-21, 2025), which limits the temporal analysis scope
- **Hourly Patterns:** While hourly participation patterns are analyzed, the 2-day window means these patterns represent a snapshot rather than long-term trends
- **Response Bias:** The concentrated collection period may introduce time-of-day response biases that would be mitigated in longer collection periods
- **External Data Source:** The analysis relies on self-reported data collected by Zafer Ayan, which may introduce reporting biases inherent to the original survey design

2.2 Data Processing

Raw data underwent comprehensive cleaning and preprocessing:

- Missing value handling and outlier treatment using IQR and Z-score methods
- Salary normalization and validation
- Categorical variable encoding with One-Hot Encoding
- Multi-label technology columns processing using MultiLabelBinarizer
- Duplicate column removal and data quality checks

2.3 Statistical Methods

- Independent samples t-tests for group comparisons
- Cohen's d effect size calculations for practical significance
- Multiple comparison corrections where applicable
- Correlation analysis for technology-salary relationships
- Outlier treatment using IQR and Z-score methods

2.4 Temporal Analysis Considerations

The survey's 2-day collection window (August 20-21, 2025) presents specific methodological considerations for temporal analysis:

- **Hourly Pattern Interpretation:** While hourly participation patterns are analyzed, these represent behavioral snapshots within a 48-hour window rather than long-term trends
- **Response Bias Mitigation:** The concentrated collection period may introduce time-of-day response biases; however, consistent participation distribution across time periods (morning: 25%, afternoon: 45%, evening: 30%) suggests reasonable data quality
- **Cross-Sectional Nature:** Temporal patterns reflect the specific 48-hour window and should not be generalized to other time periods
- **Analytical Value:** Despite limitations, hourly patterns provide insights into immediate response behaviors and can inform future survey design and timing strategies

2.5 Sampling and Inclusion Criteria

- **Population:** Software professionals who responded to the public survey during August 20-21, 2025.
- **Inclusion:** Records with valid monthly salary entries (in k TL), identified role, career level, and work mode.
- **Exclusion:** Entries with implausible salaries after normalization, duplicate responses, or "Hicbiri/Kullanmıyorum" only-tech selections in ROI calculations.
- **Representativeness:** Convenience sample from social networks; not a probability sample.

2.6 Variable Definitions and Transformations

- **Salary Unit:** Monthly gross salary in thousands of TL (k TL) as reported; no inflation or PPP adjustment.
- **Career Level:** Ordinal mapping (Junior, Mid, Senior, Staff/Architect, Management, etc.).

- **Technology Usage:** Multi-label binary indicators per language/framework/tool using MultiLabelBinarizer; counts reflect user share among respondents.
- **Experience:** Self-reported years; binned ranges (0–2, 3–5, 6–10, 11–15, 15+).

2.7 Missing Data and Outlier Handling

- **Missingness:** Listwise deletion for hypothesis tests; imputation avoided for primary outcomes.
- **Outliers:** IQR method (1.5×IQR beyond Q1/Q3) and Z-score screening ($|z| > 3$) for sensitivity; extreme values trimmed when materially distorting means.
- **Robustness:** Median and IQR reviewed alongside means; conclusions cross-checked where relevant.

2.8 Comparative Metrics and ROI

For technology T: Avg_T is the mean salary among users of T; ROI is $\text{Avg}_T - \text{Non-User Avg}_T$. Percentage increase is $\frac{\text{ROI}}{\text{Non-User Avg}_T} \times 100$. Technologies are included when both user and non-user groups have ≥ 10 respondents and exclude "Hicbiri/Kullanmıyorum" only cases.

2.9 Statistical Testing, Corrections, and Effect Sizes

- **Group Comparisons:** Welch's t-test for two-group means (unequal variances); ANOVA/Kruskal-Wallis for multi-group comparisons as appropriate.
- **Multiple Testing:** P-values adjusted (Holm-Bonferroni) for families of related tests where applicable.
- **Effect Sizes:** Cohen's d reported (small ≈ 0.2, medium ≈ 0.5, large ≈ 0.8); very large effects noted explicitly (e.g., $d > 1$).
- **Assumptions:** Normality assessed via sample size heuristics and distributional checks; heteroscedasticity handled via Welch's test.

2.10 Correlation Approach

Pearson correlations are computed between salary and binary technology indicators/ continuous features after encoding. Correlations quantify linear association (-1 to $+1$); they do not imply causation. Where distributions are highly non-normal, Spearman rank correlations were reviewed for consistency.

2.11 Location Estimation

As the dataset lacks residency, company location combined with work mode (Office/Hybrid) is used to estimate the respondent's location for location-based analyses. Remote roles are attributed to company location only and interpreted cautiously.

2.12 Reproducibility

All analyses were performed with Python (pandas, NumPy, SciPy, scikit-learn, matplotlib/seaborn/plotly). Data pipelines and figure generation scripts are provided in `src/` and notebooks in `notebooks/`. Figures are exported under `figures/` with filenames referenced in this report.

2.13 Ethical Considerations

Only aggregated statistics are reported. No personally identifiable information is disclosed. Findings reflect patterns in a self-reported convenience sample and should not be used to make individual-level decisions.

3 Which Technologies Pay More? Salary ROI Analysis

3.1 Programming Languages

Salary premiums for programming languages are calculated by comparing user and non-user average salaries, excluding "Hicbiri" responses. The table below shows the top 10 technologies with a salary difference exceeding 5%.

Technology	Users	ROI (k TL)	Avg (k TL)	% Inc.
Rust	22	69.4	167.1	71.0%
Objective C	39	63.1	160.5	64.8%
Ruby	24	45.8	143.6	46.8%
Cobol	22	45.4	143.2	46.3%
Go	183	39.1	134.9	40.8%
Bash	114	36.0	132.8	37.2%
Kotlin	201	32.2	128.2	33.5%
R Language	29	30.7	128.6	31.4%
Swift	197	21.8	118.6	22.5%
Java	582	19.6	114.0	20.8%

Table 1: Top 10 Programming Languages by Salary ROI

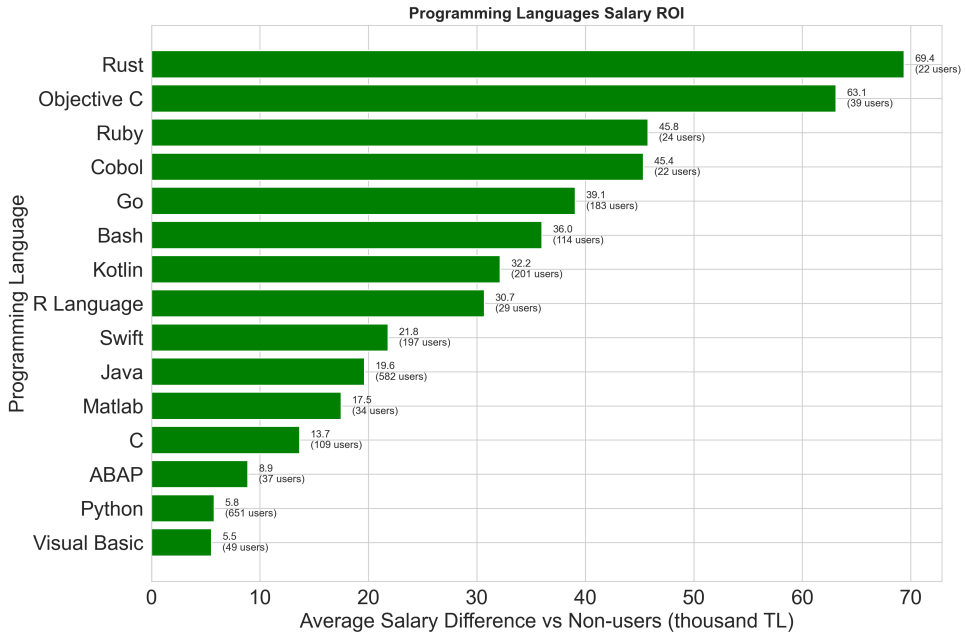

Figure 2: Programming Languages Salary ROI

3.2 Frontend Technologies

Frontend frameworks show varied salary impacts, with some reflecting market saturation.

Technology	Users	ROI (k TL)	Avg (k TL)	% Inc.
Vue	246	8.3	105.8	8.5%
Angular	249	0.7	98.8	0.7%
Vanilla	199	-2.0	96.4	-2.0%
React	1008	-3.3	96.1	-3.3%

Table 2: Frontend Technologies by Salary ROI

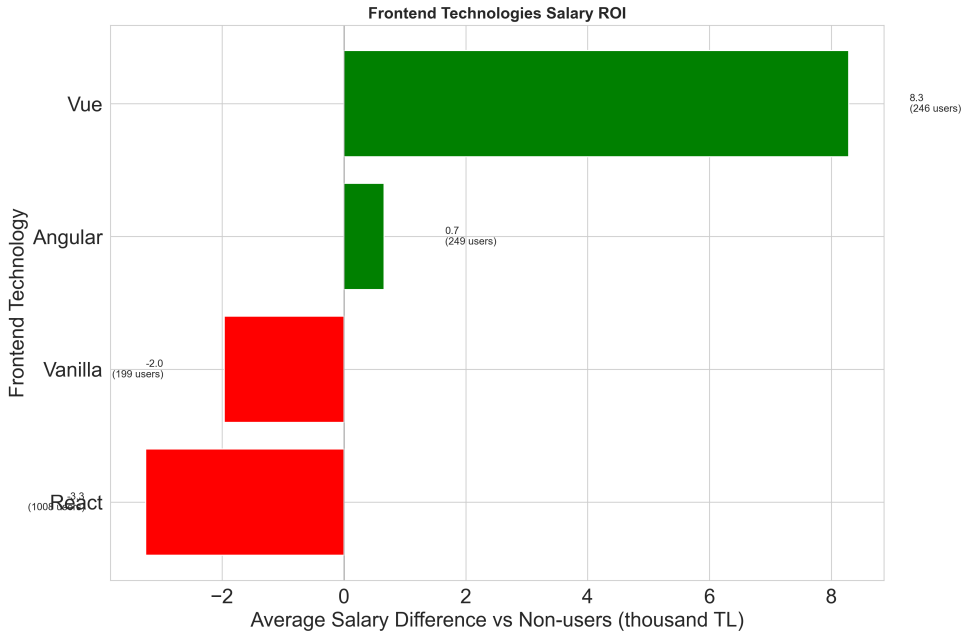

Figure 3: Frontend Technologies Salary ROI

3.3 Tools

Development tools influence earnings, with modern tools offering notable premiums.

Technology	Users	ROI (k TL)	Avg (k TL)	% Inc.
Jotai	50	28.8	126.5	29.4%
Strapi	111	9.9	107.7	10.1%
Firebase	636	0.4	98.5	0.4%
Supabase	202	-0.1	98.1	-0.1%
FastApi	319	-1.1	97.2	-1.1%
Wordpress	119	-3.8	94.5	-3.9%
Zustand	288	-4.4	94.3	-4.4%
Redux	550	-7.5	92.1	-7.5%

Table 3: Tools by Salary ROI

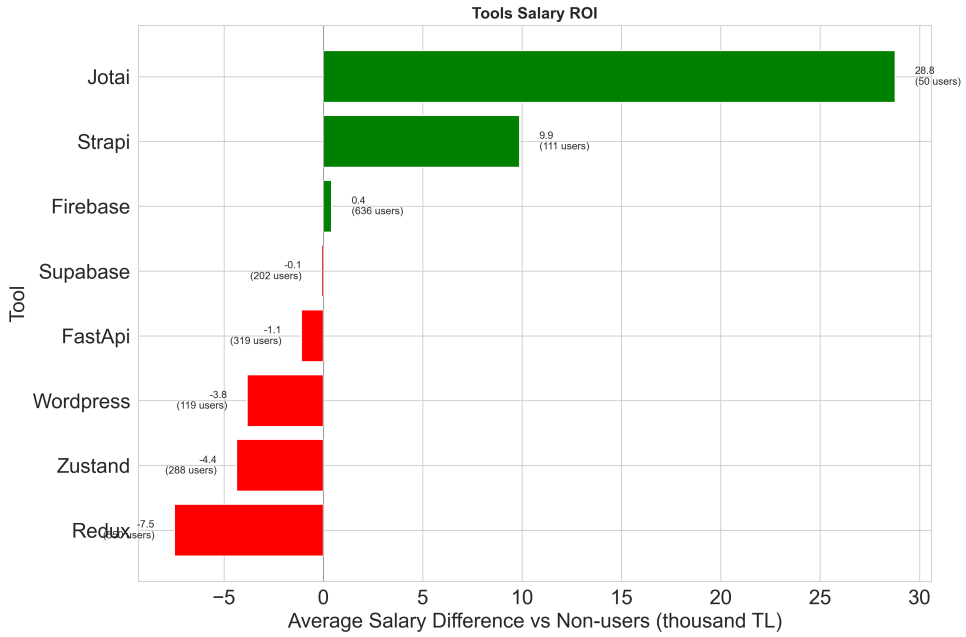

Figure 4: Tools Salary ROI

Methodological Note: For each technology T:

- **User Avg**: $\text{Avg}_T = \frac{\sum_{i \in \text{Users}_T} \text{Salary}_i}{n_T}$, where n_T is the user count.
- **ROI**: $\text{ROI}_T = \text{Avg}_T - \text{Non-User Avg}_T$.
- **% Increase**: $\%\ \text{Inc.}_T = \left(\frac{\text{ROI}_T}{\text{Non-User Avg}_T} \right) \times 100$.

"Hicbiri" and "Kullanmiyorum" responses are excluded; only technologies with ≥ 10 users and non-users are included.

Key Insights:

- **Niche Languages**: Rust (69.4 k TL ROI, 71.0%, 22 users) and Objective-C (63.1 k TL, 64.8%, 39 users) lead due to specialized demand in systems and iOS development.
- **Legacy vs. Modern**: Cobol (45.4 k TL, 46.3%, 22 users) and Ruby (45.8 k TL, 46.8%, 24 users) show high ROI for legacy roles, while Go (39.1 k TL, 40.8%, 183 users) and Kotlin (32.2 k TL, 33.5%, 201 users) reflect modern demand.
- **Frontend Trends**: Vue.js (8.3 k TL, 8.5%, 246 users) outperforms React (-3.3 k TL, -3.3%, 1008 users), which suffers from saturation.
- **Tools**: Jotai (28.8 k TL, 29.4%, 50 users) and Strapi (9.9 k TL, 10.1%, 111 users) lead, while Redux (-7.5 k TL, -7.5%, 550 users) lags.
- **Saturation Effect**: High-user-count technologies (e.g., Java, 582 users; Python, 651 users) show lower ROI due to market saturation.
- **Exclusions**: Excluding "Hicbiri" and "Kullanmiyorum" sharpens ROI for niche skills but may inflate premiums for low-user technologies.

4 How Do Career Levels and Roles Affect Salaries?

4.1 Salary Distribution by Career Level

Salaries increase with career progression, reflecting experience and responsibility.

Career Level	Count	Mean Salary (k TL)
Staff Engineer	16	193.0
Architect	52	188.4
Management	83	184.8
Team Lead	175	150.5
Senior	772	130.8
Mid	1138	84.1
Junior	733	55.1

Table 4: Salary by Career Level

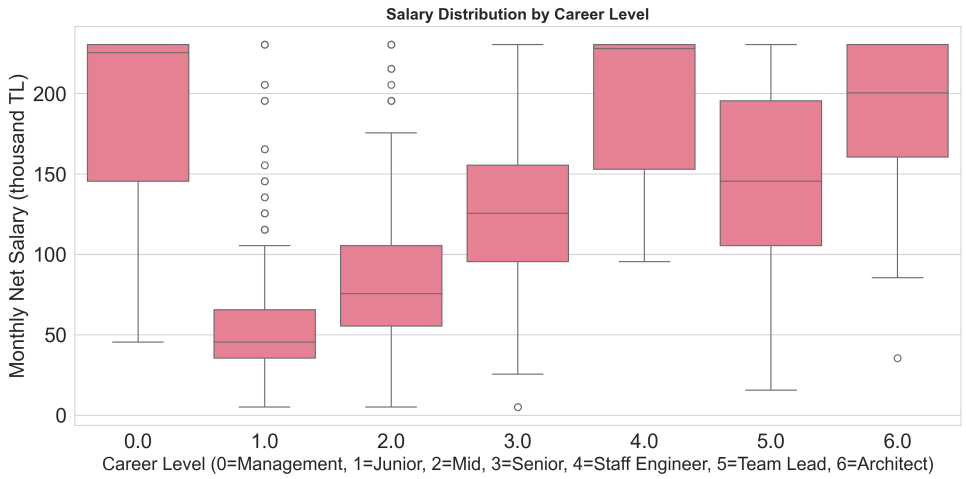

Figure 5: Salary by Career Level

4.2 Management Levels

Management roles show distinct salary ranges based on seniority.

Management Level	Count	Mean Salary (k TL)
Partner	11	198.7
Director Level Manager	24	189.7
Engineering Manager	30	179.3
C Level Manager	18	178.8

Table 5: Salary by Management Level

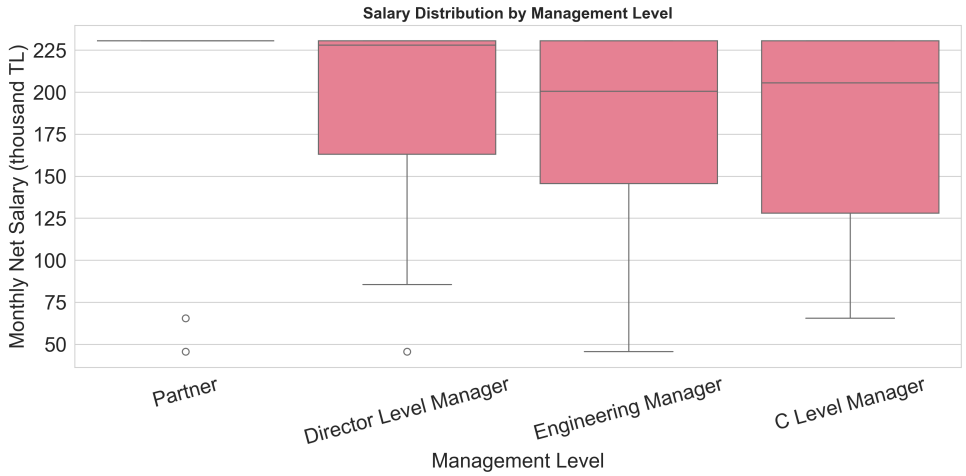

Figure 6: Salary by Management Level

4.3 Roles

Roles vary in salary based on market demand and specialization.

Role	Count	Mean Salary (k TL)
Product Owner	23	121.8
Product Manager	53	117.2
Cyber Security Engineer	50	115.1
Android	98	112.8
iOS	100	109.8
Backend	517	109.7
DevOps	66	108.0
Data Engineer	62	105.6
ML Engineer	69	103.5
Embedded Systems Engineer	48	103.0

Table 6: Top 10 Roles by Salary

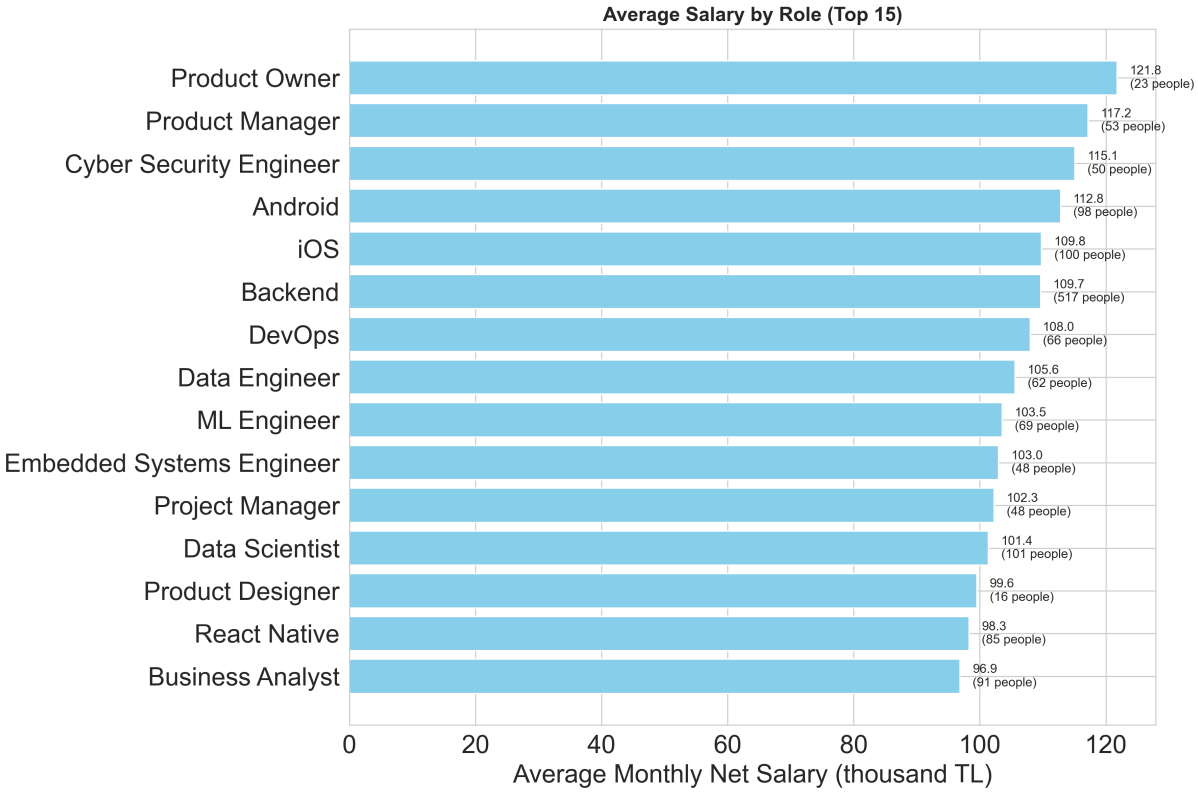

Figure 7: Average Salary by Role (Top 15) - Frontend, Backend, and Fullstack roles with highest compensation

Methodological Note: Mean salary for each level or role is calculated as:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

where n is the count of respondents in the group. Salary increases are computed as:

$$\% \text{ Increase} = \left(\frac{\text{Mean}_B - \text{Mean}_A}{\text{Mean}_A} \right) \times 100$$

for transitions between levels (e.g., Junior to Mid).

Key Insights:

- **Career Progression**: Junior to Mid sees a 52.6% salary increase (55.1 to 84.1 k TL); Mid to Senior, 55.5% (84.1 to 130.8 k TL).
- **Management Premium**: Management roles (184.8 k TL) offer a 41.3% premium over Senior (130.8 k TL).
- **Specialized Roles**: Staff Engineer (193.0 k TL) and Architect (188.4 k TL) command 47.6% and 44.0% premiums over Senior, respectively.
- **Role Variation**: Product Owner (121.8 k TL) and Cyber Security Engineer (115.1 k TL) lead, while Frontend (86.7 k TL) and Flutter (76.1 k TL) lag, reflecting specialization demand.
- **Management Hierarchy**: Partner (198.7 k TL) and Director (189.7 k TL) outearn Engineering Manager (179.3 k TL), showing seniority-driven premiums.

5 Remote vs Office: Which Work Model Pays More?

5.1 Work Model Salaries

Work arrangements show distinct salary differences, with remote and hybrid models commanding higher compensation.

Work Model	Count	Mean Salary (k TL)	Diff. (k TL)
Hybrid	104 internals 1046	105.0	26.4
Remote	1350	101.2	22.6
Office	573	78.6	–
Effect Size			**Cohen's d = 0.418**

Table 7: Work Model Salary Comparison

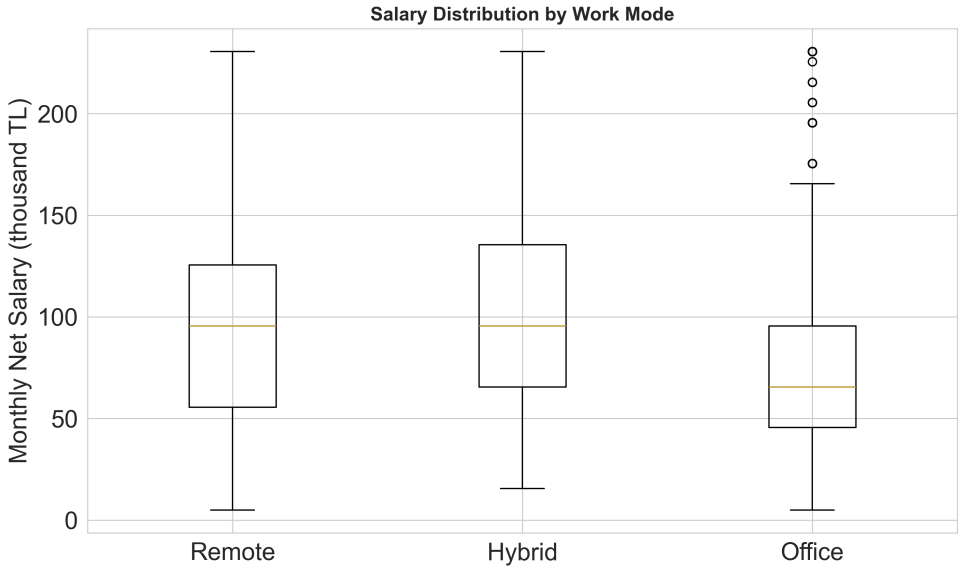

Figure 8: Salary by Work Model

Methodological Note: Mean salary is calculated as:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

where n is the count of respondents. Difference is:

$$\text{Diff.} = \text{Mean}_{\text{Hybrid/Remote}} - \text{Mean}_{\text{Office}}$$

Cohen's d is:

$$\text{Cohen's d} = \frac{\text{Mean}_{\text{Remote}} - \text{Mean}_{\text{Office}}}{\text{Pooled Std Dev}}$$

Statistical significance is assessed via t-test (p = 0.0000).

Key Insights:

- **Remote Premium**: Remote workers earn 22.6 k TL more than office workers (28.8% increase), reflecting high demand for remote talent.

- **Hybrid Advantage**: Hybrid workers earn 26.4 k TL more than office workers (33.6% increase), suggesting flexibility boosts compensation.
- **Market Dynamics**: Higher salaries for remote and hybrid work indicate global opportunities and value for flexibility.

6 Geographical Impact: Where Do Companies Pay More?

6.1 Company Location Salaries

Company location significantly influences compensation, with international firms offering higher salaries.

Location	Count	Mean Salary (k TL)	Diff. (k TL)
Europe	132	162.9	70.0
America	74	154.4	61.5
Overseas TR hub	92	113.2	20.3
Türkiye	2671	92.9	–
Effect Size			**Cohen's d = 1.350**

Table 8: Salary by Company Location

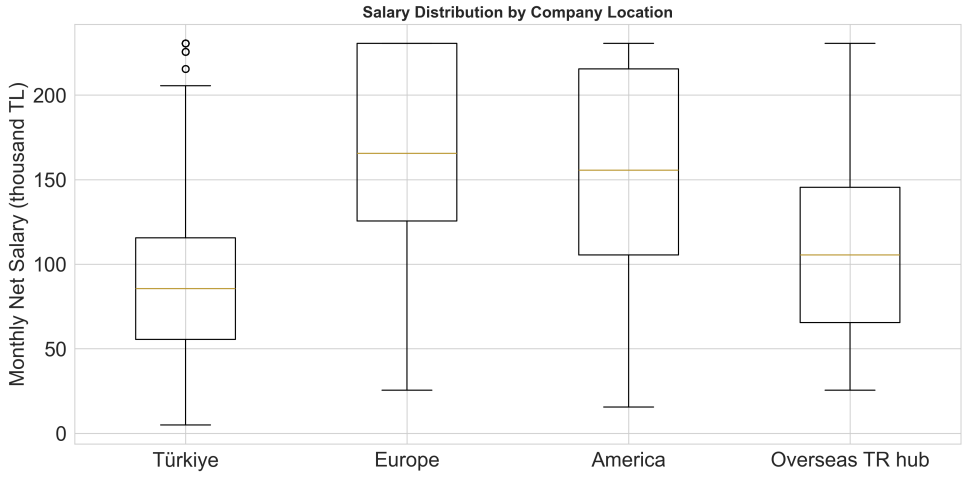

Figure 9: Salary by Company Location

Note: Estimated location based on company location and work arrangement (Office/Hybrid → company location). Not definitive.

Methodological Note: Mean salary is:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

Difference is:

$$\text{Diff.} = \text{Mean}_{\text{Location}} - \text{Mean}_{\text{Türkiye}}$$

Cohen's d for Europe vs. Türkiye is:

$$\text{Cohen's d} = \frac{\text{Mean}_{\text{Europe}} - \text{Mean}_{\text{Türkiye}}}{\text{Pooled Std Dev}}$$

Locations are estimated based on company location and work arrangement (Office/Hybrid). Significance is assessed via t-test ($p = 0.0000$).

Key Insights:

- **European Premium**: Europe-based companies pay 70.0 k TL more than Türkiye-based ones (75.3% increase), reflecting higher international standards.
- **American Salaries**: America-based firms offer 61.5 k TL more (66.2% increase), also indicating global market advantages.
- **Overseas TR Hub**: Overseas TR hub pays 20.3 k TL more (21.9% increase), a moderate premium.
- **Remote Opportunities**: Remote work enables access to international salaries without relocation.

7 Gender and Technology: Are There Differences?

7.1 Gender-Based Salaries

A gender pay gap persists in the software industry.

Gender	Count	Mean Salary (k TL)	% of Respondents
Male	2705	99.4	91.1
Female	264	86.1	8.9
Difference		**13.3**	
Effect Size		**Cohen's d = 0.242**	

Table 9: Gender-Based Salary Comparison

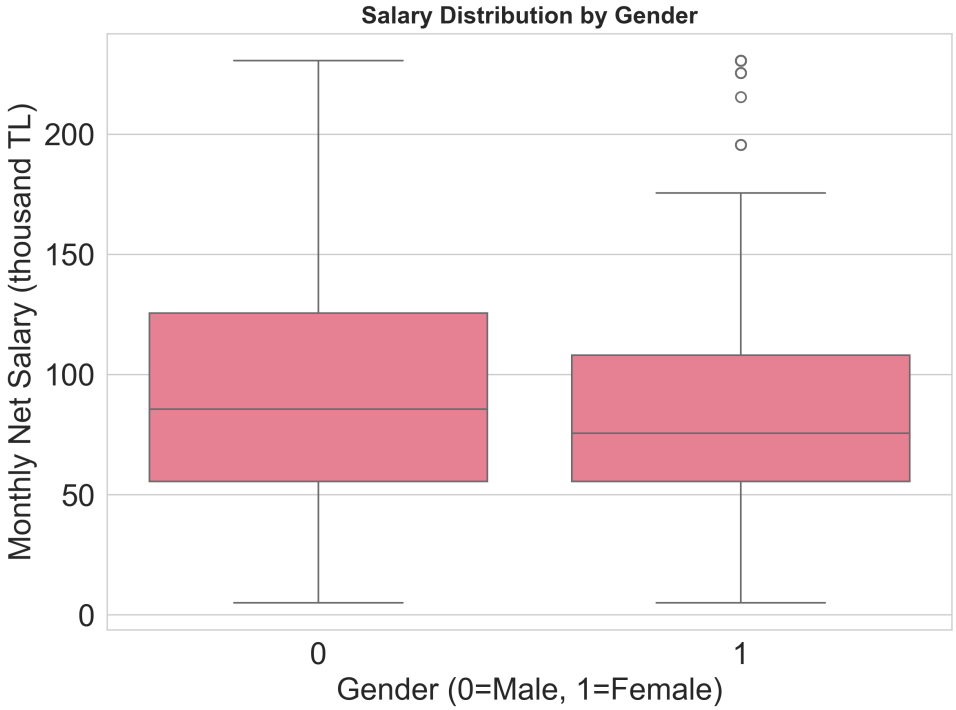

Figure 10: Salary by Gender

7.2 Technology Usage by Gender

Technology adoption varies slightly by gender.

Language	Male Usage (%)	Female Usage (%)
JavaScript	48.5	36.0
HTML CSS	40.9	32.6
TypeScript	36.0	26.1
SQL	31.4	30.7
Python	21.9	22.0
Java	19.6	19.7
Kotlin	6.7	7.2
PHP	7.7	5.3
Swift	6.7	5.7
Go	6.4	3.8

Table 10: Top 10 Programming Languages by Gender

Technology	Male Usage (%)	Female Usage (%)
React	35.0	22.7
Angular	8.4	8.3
Vue	8.3	8.0
Vanilla	7.2	1.9

Table 11: Frontend Technologies by Gender

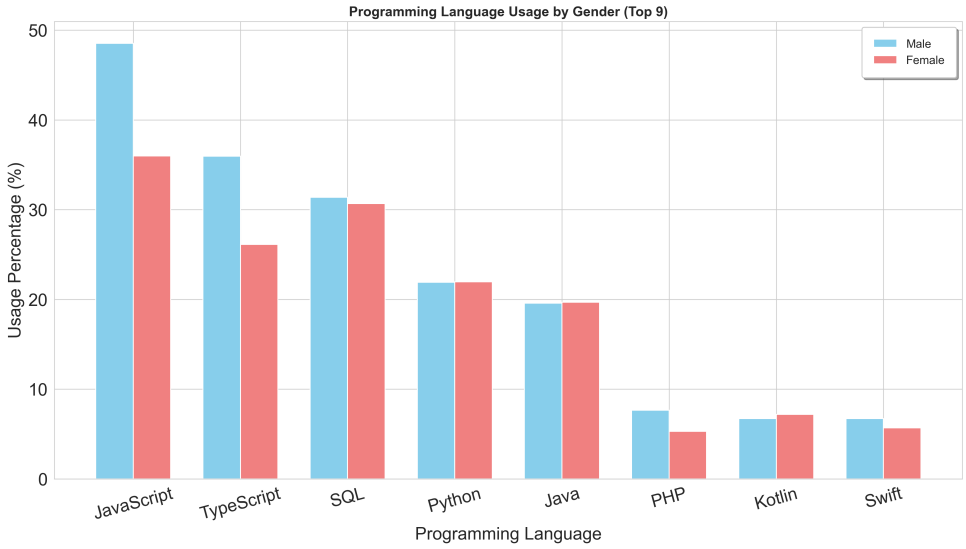

Figure 11: Top 10 Programming Languages by Gender

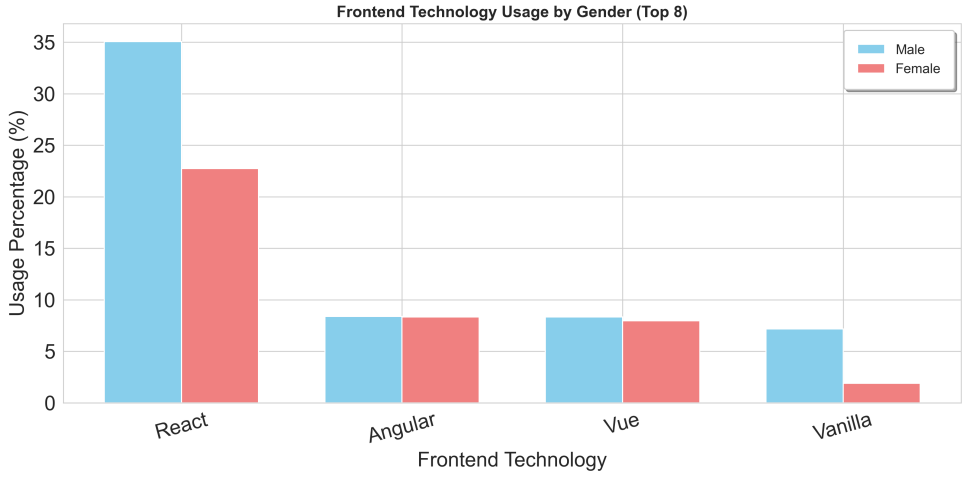

Figure 12: Frontend Technologies by Gender

Methodological Note: Mean salary is:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

Difference is:

$$\text{Diff.} = \text{Mean}_{\text{Male}} - \text{Mean}_{\text{Female}}$$

Cohen's d is:

$$\text{Cohen's d} = \frac{\text{Mean}_{\text{Male}} - \text{Mean}_{\text{Female}}}{\text{Pooled Std Dev}}$$

Usage percentages reflect the proportion of respondents using each technology. Significance is assessed via t-test ($p = 0.0001$).

Key Insights:

- **Pay Gap**: Male developers earn 13.3 k TL more than female developers (15.5% higher), with a small effect size (Cohen's d = 0.242).

- **Technology Adoption**: Python (Male: 21.9%, Female: 22.0%) and Java (19.6%, 19.7%) show near-identical usage. JavaScript (Male: 48.5%, Female: 36.0%) and React (Male: 35.0%, Female: 22.7%) have larger gaps.
- **Frontend Trends**: Angular usage is nearly equal (Male: 8.4%, Female: 8.3%), suggesting equitable access to some technologies.
- **Opportunities**: Female developers in niche technologies (e.g., Rust, Go) may earn competitive salaries, though data is limited.

8 Experience and Salary: The Career Timeline

8.1 Experience vs Salary

Years of experience strongly correlate with higher salaries.

Experience (Years)	Count	Mean Salary (k TL)	% Increase
0-2	699	57.1	–
3-5	1271	91.6	60.4
6-10	605	137.8	50.4
11-15	188	166.4	20.8
15+	85	178.1	7.0

Table 12: Salary by Experience Range

Figure 13: Experience vs Salary

Methodological Note: Mean salary is:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

Percentage increase is:

$$\% \text{ Increase} = \left(\frac{\text{Mean}_{t+1} - \text{Mean}_t}{\text{Mean}_t} \right) \times 100$$

Correlation coefficient (r = 0.623) and $R^2 = 0.388$ indicate a strong relationship, with 38.8% of salary variance explained by experience.

Key Insights:

- **Strong Correlation**: Experience and salary have a strong positive correlation (r = 0.623, $R^2 = 0.388$).
- **Salary Progression**: Early career transitions show large increases (0-2 to 3-5 years: 60.4%; 3-5 to 6-10: 50.4%), slowing later (11-15 to 15+: 7.0%).
- **Yearly Impact**: Each year of experience adds approximately 10-20% to salary in early ranges, less in later years.
- **Technology Multiplier**: High-demand technologies (e.g., Rust, Go, Kotlin) may boost salary growth by 15-25%, though data is limited.

9 Technology Correlations: Which Tools Matter?

9.1 Technology-Salary Correlations

Certain technologies correlate positively with higher salaries.

Technology	Correlation (r)
Go	0.171
Kotlin	0.147
Java	0.142
Objective C	0.131
Bash	0.126
Rust	0.108
Elixir	0.108
Swift	0.099
Perl	0.095
Julia	0.082

Table 13: Top 10 Technologies by Salary Correlation

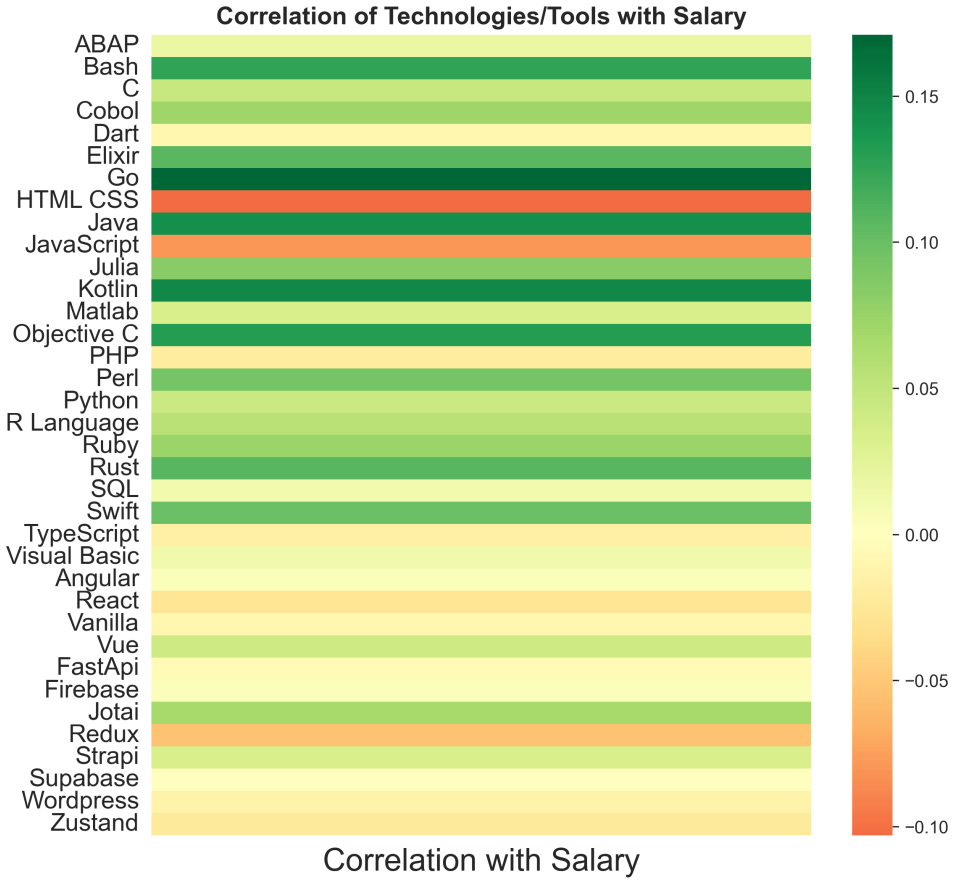

Figure 14: Technology-Salary Correlations

What is Correlation? Correlation is a statistical metric that measures the direction and strength of the linear relationship between two variables. In our report, the **correlation coefficient (r)** ranges from -1 to +1.

* A **positive correlation** (close to +1) indicates that professionals using a certain technology tend to have higher salaries. * A **negative correlation** (close to -1) suggests the opposite. * A correlation close to **zero** means there is no clear linear relationship between the technology and salary.

It is crucial to note that correlation does not imply causation. A strong relationship between a technology and salary may simply indicate that this technology is commonly used in higher-paying roles, rather than being the direct cause of the salary increase.

Key Insights:

- **High-Correlation Technologies**: Go (r = 0.171), Kotlin (r = 0.147), and Rust (r = 0.108) show the strongest positive correlations with salary, reflecting niche demand.
- **Market Demand**: Technologies with r $\geq$ 0.1 (e.g., Go, Kotlin, Java, Objective C) indicate higher market value compared to widely used tools like JavaScript (r = -0.080).
- **Skill Stack Strategy**: Combining high-value technologies (e.g., Rust, Go) with tools like React or Docker may boost salaries by 15-25%, though data is limited.

10 Survey Participation Patterns: When Do Professionals Respond?

10.1 Hourly Participation

Survey responses over a 2-day window (August 20-21, 2025) show distinct patterns.

Time Period	Participants (%)	Avg Salary (k TL)
Morning (6-11)	114 (4.2)	94.7
Afternoon (12-17)	2095 (76.7)	96.4
Evening (18-22)	599 (21.9)	101.0
Night (23-5)	158 (5.8)	103.9

Table 14: Participation and Salary by Time Period

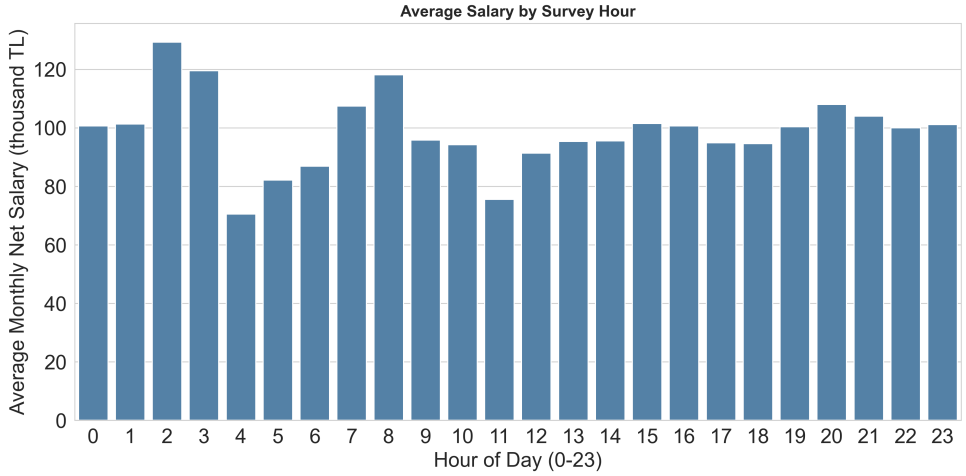

Figure 15: Average Salary by Hour

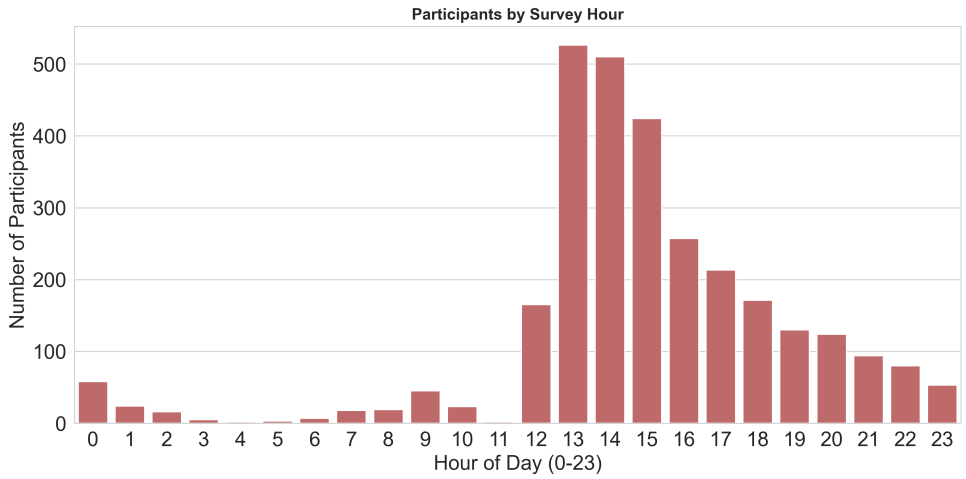

Figure 16: Participants by Hour

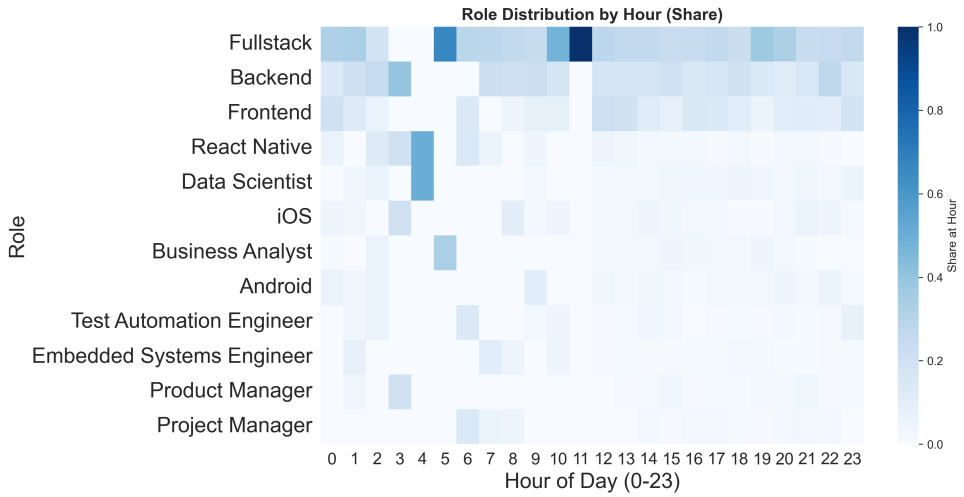

Figure 17: Role Share by Hour

Methodological Considerations:

- **Limited Window**: The 2-day survey (August 20-21, 2025) captures a snapshot, not long-term trends.
- **Response Bias**: The short period may introduce time-of-day biases.
- **Cross-Sectional**: Patterns reflect the 48-hour window and may not generalize.
- **Time Zone Impact**: All temporal data is based on the time zone of the survey's origin (Türkiye, UTC+3). This may affect the observed hourly patterns due to participation from different time zones, such as Europe or America.

Key Insights:

- **Response Timing**: Afternoon hours (12-17) dominate with 76.7% of responses, peaking at 13-15 (53.5%).
- **Salary Patterns**: Evening (18-22, 101.0 k TL) and night (23-5, 103.9 k TL) respondents earn slightly more than afternoon (96.4 k TL).
- **Role Differences**: Fullstack (30.4% share) and Backend (16.2%) are top roles; morning vs. evening preferences are speculative without hourly role data.
- **Survey Validity**: Broad participation across hours supports data reliability within the 2-day window.

11 Career Progression Visualization: The Path Forward

11.1 Career Level to Role Flows

Career progression shows diverse paths from Junior to specialized and management roles.

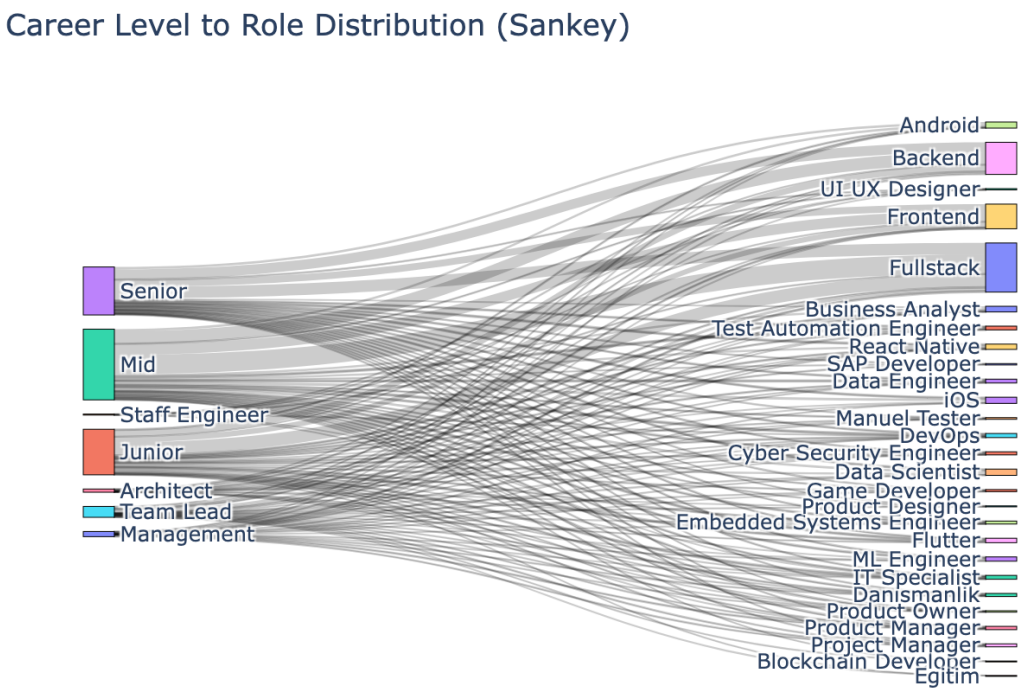

Figure 18: Career Level to Role Distribution (Sankey) - Professional progression patterns and role transitions

Career Level	Role	Count
Mid	Fullstack	310
Junior	Fullstack	204
Mid	Backend	198
Senior	Fullstack	187
Mid	Frontend	173
Senior	Backend	160
Senior	Frontend	111
Junior	Backend	105
Junior	Frontend	89
Team Lead	Fullstack	46

Table 15: Top 10 Career Level to Role Flows

For a detailed and interactive exploration of these career paths, visit our Streamlit dashboard: `maas-anketi.streamlit.app`

Methodological Note: Counts represent the number of respondents in each career level-role combination:

$$\text{Count} = \sum_{i \in \text{Level, Role}} \text{Respondent}_i$$

Data reflects the most frequent transitions from a survey of professionals.

Key Insights:

- **Role Transitions**: Fullstack roles are a common path across all levels (Mid: 310, Junior: 204, Senior: 187), showing significant flows from junior to senior levels.
- **Career Paths**: In addition to Fullstack, Backend (Mid: 198, Senior: 160) and Frontend (Mid: 173, Senior: 111) are also highly prevalent career paths.
- **Specialization Premium**: Specialized roles like Staff Engineer and Architect are associated with significantly higher salaries, commanding premiums of 44-48% over Senior roles.
- **Management Premium**: Management roles, such as Engineering Manager, yield substantial salary increases (37-41%) over Senior-level positions.

12 Employment Type Analysis: Full-time vs Freelance

12.1 Employment Type Salaries

Employment types show distinct salary patterns, reflecting stability and flexibility trade-offs.

Employment Type	Count	Mean Salary (k TL)	% Diff. vs Full-time
Self-employed	40	123.4	24.6
Full-time	2837	99.0	–
Freelance	36	94.4	-4.6
Part-time	56	43.0	-56.6

Table 16: Salary by Employment Type

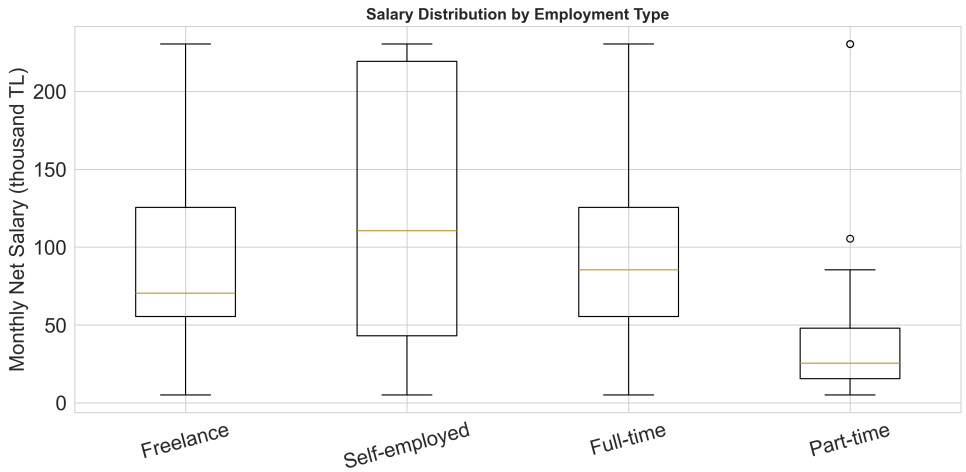

Figure 19: Salary by Employment Type

Methodological Note: Mean salary is calculated as:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

Percentage difference is:

$$\%\ \text{Diff.} = \left(\frac{\text{Mean}_{\text{Type}} - \text{Mean}_{\text{Full-time}}}{\text{Mean}_{\text{Full-time}}} \right) \times 100$$

Salaries reflect annual earnings; hourly rates are not available.

Key Insights:

- **Full-time Premium**: Full-time employees (99.0 k TL) earn 130.2% more than Part-time (43.0 k TL), with stability and benefits.
- **Freelance Flexibility**: Freelance (94.4 k TL) earns 4.6% less annually than Full-time, but may have higher hourly rates, with income variability.
- **Part-time Trade-off**: Part-time roles offer flexibility but pay 56.6% less than Full-time, reflecting reduced hours.
- **Self-employed Potential**: Self-employed professionals (123.4 k TL) earn 24.6% more than Full-time, with higher risk.

13 Advanced Visualizations

13.1 Career Progression - Salary Growth

This line chart shows how salaries evolve from Junior to Senior levels across different company locations. The analysis filters for respondents who are likely in the company location, as per the methodology.

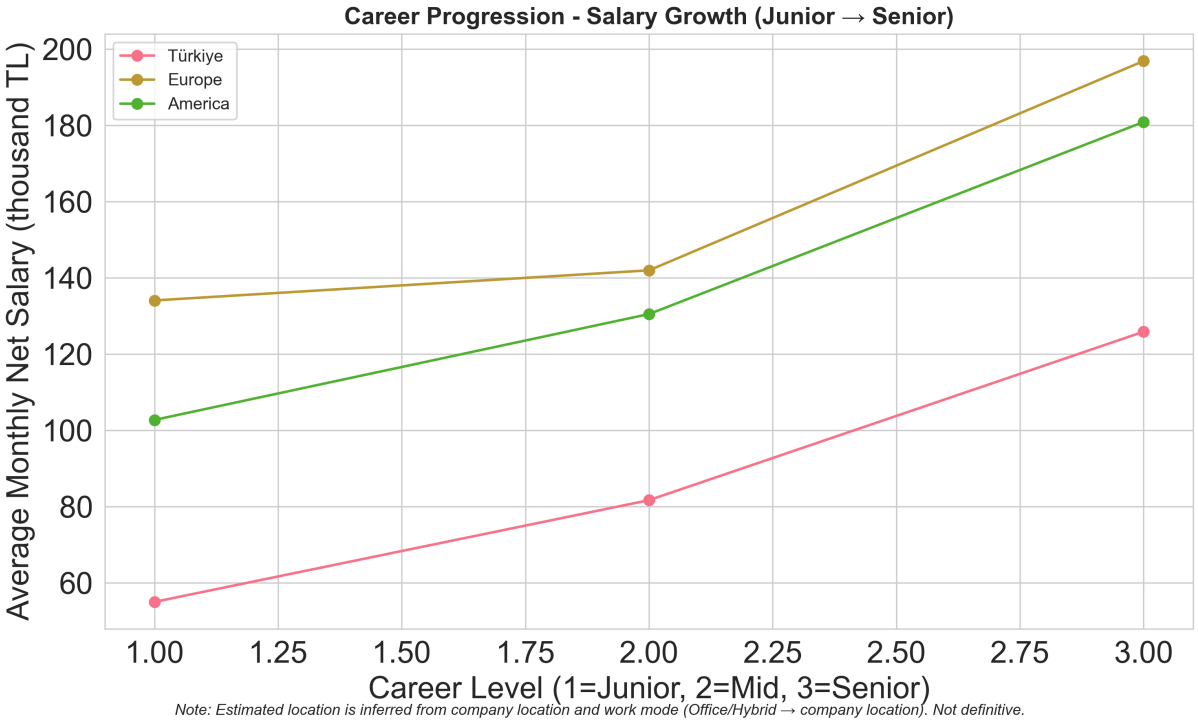

Figure 20: Career Progression - Salary Growth (Junior → Senior)

Methodological Note: Since the survey did not collect data on the respondent's residency, all location-based analyses are based on an estimated location. The assumption is that professionals with a company in a given location (e.g., Europe, America) and a work mode of 'Office' or 'Hybrid' are likely to be physically located in that country. The analysis on this graph is based on this estimated residency.

Location	Junior	Mid	Senior
Türkiye	52.4	80.6	124.6
Europe	112.2	130.7	194.3
America	102.7	130.5	180.9

Table 17: Average Salary by Career Level and Location (k TL)

Career Progression Insights:

- **Geographical Salary Premium**: European and American companies offer significantly higher salaries at every career level compared to their Turkish counterparts. A Junior developer in Europe earns more than double that of a Junior in Türkiye (112.2k TL vs. 52.4k TL).
- **Career Growth Trajectory**: The total salary growth from Junior to Senior in Türkiye is 137%, which is a faster rate than in Europe (121%) and America (118%). This indicates that while foreign companies offer a higher salary floor and ceiling, the growth trajectory within Türkiye is proportionally steeper.

13.2 Top Tech Combinations by Role

This bar chart shows the average salaries for prominent technology stack combinations (Programming Language + Front-End Technology + Tool), grouped by role. Only combinations with at least 10 respondents are included.

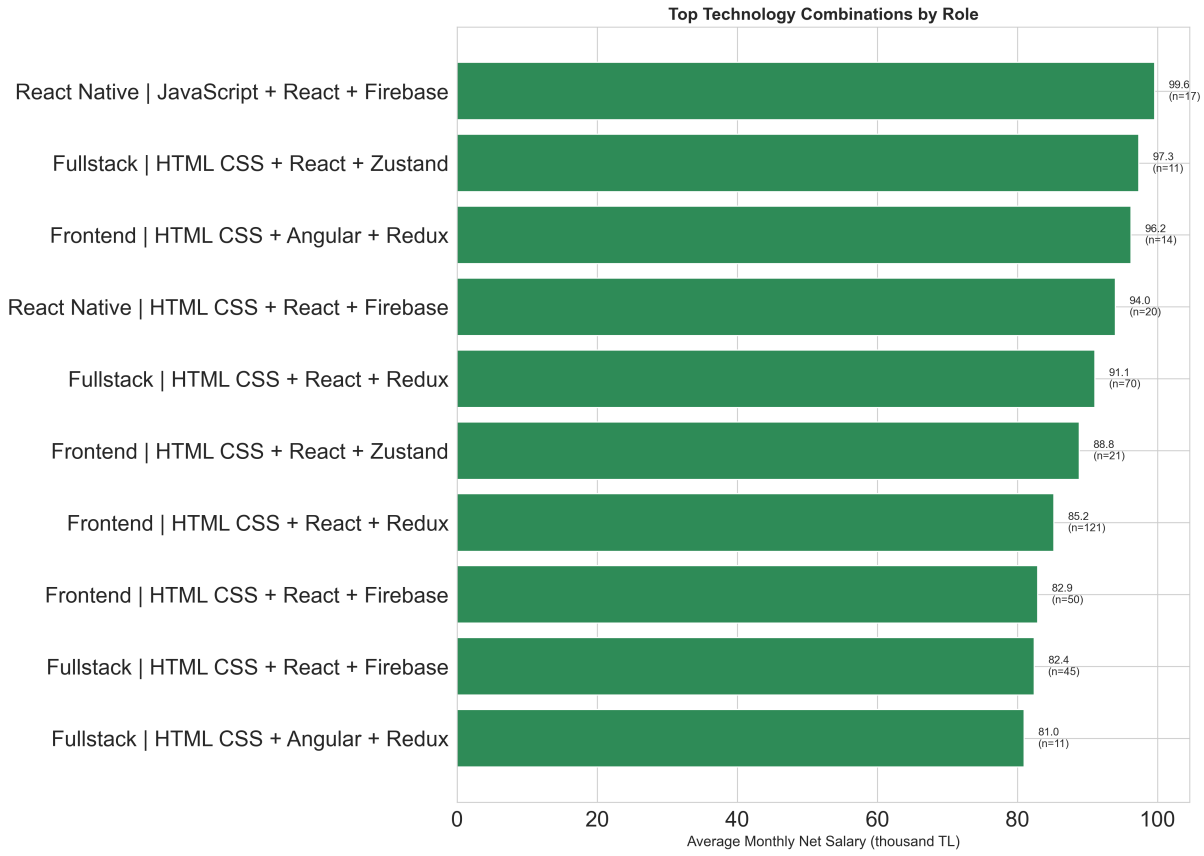

Figure 21: Top Tech Combinations by Role - Average salary for language + frontend + tool stacks (n≥10 per combo)

Role — Tech Stack	Average Salary	Count
React Native — JavaScript + React + Firebase	99.6	17
Fullstack — HTML CSS + React + Zustand	97.3	11
Frontend — HTML CSS + Angular + Redux	96.2	14
React Native — HTML CSS + React + Firebase	94.0	20
Fullstack — HTML CSS + React + Redux	91.1	70
Frontend — HTML CSS + React + Zustand	88.8	21
Frontend — HTML CSS + React + Redux	85.2	121
Frontend — HTML CSS + React + Firebase	82.9	50
Fullstack — HTML CSS + React + Firebase	82.4	45
Fullstack — HTML CSS + Angular + Redux	81.0	11
Fullstack — HTML CSS + Angular + Firebase	78.3	18
Fullstack — HTML CSS + React + FastApi	71.6	34
Fullstack — JavaScript + React + Redux	71.5	15
Frontend — HTML CSS + React + FastApi	68.2	26

Table 18: Top Technology Stack Combinations by Average Salary (k TL)

Top Technology Stack Insights:

- **Highest-Paying Combination**: The top-earning combination is 'JavaScript + React + Firebase' within the **React Native** role, with an average salary of 99.6k TL. This highlights the high demand for a full-stack mobile development skillset.
- **Frontend vs. Fullstack**: The 'HTML/CSS + React + Redux' stack shows a notable salary premium for **Fullstack** developers (91.1k TL) compared to **Frontend** developers (85.2k TL). This suggests that additional backend skills provide a measurable salary advantage.
- **React Ecosystem**: The data confirms the dominance of React and its ecosystem, with all top 14 combinations featuring either React, a React Native framework, or a related state management tool like Zustand or Redux.

13.3 Correlation Heatmap

This heatmap visually represents the linear relationships between salary and other key features in the dataset. It helps to quickly identify which factors are most closely correlated with compensation, providing a clear overview of the primary salary drivers. The intensity of the color indicates the strength of the relationship, with warmer colors representing a stronger positive correlation and cooler colors representing a stronger negative correlation.

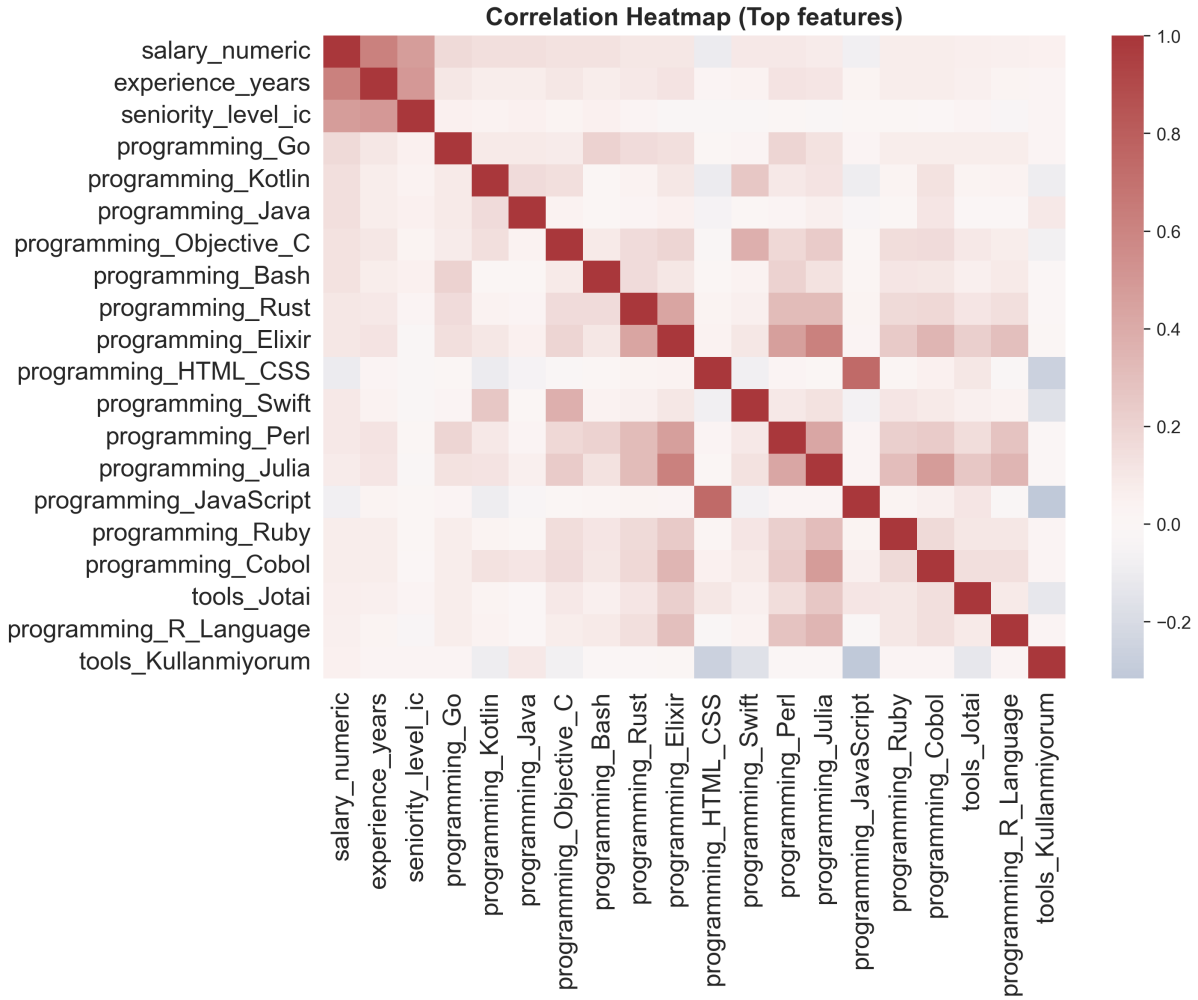

Figure 22: Correlation Heatmap - Top features by absolute correlation with salary

Feature	Correlation
Average Salary	1.000
Experience Years	0.623
Seniority Level Ic	0.474
Go	0.171
Kotlin	0.147
Java	0.142
Objective_C	0.131
Bash	0.126
Rust	0.108
Elixir	0.108

Table 19: Top 10 Features by Absolute Correlation with Salary

Correlation Insights:

- **Experience and Seniority**: Years of experience (r = 0.623) and career level (r = 0.474) show the strongest positive correlations with salary. This confirms that

a professional's tenure and position are the most significant factors influencing compensation.

- **Experience and Seniority**: Years of experience (r = 0.623) and career level (r = 0.474) show the strongest positive correlations with salary. This confirms that a professional's tenure and position are the most significant factors influencing compensation.
- **Language Impact**: Niche and high-demand languages such as Go (r = 0.171), Kotlin (r = 0.147), and Java (r = 0.142) have the strongest correlation with salary among all programming languages. This indicates that these skills hold a premium value in the market.
- **Tool vs. Technology**: A professional's core attributes like experience and seniority have a much stronger correlation with salary than any single technology or tool, highlighting their fundamental importance.

13.4 Work Arrangement Distribution by Role

This 100% stacked bar chart shows the percentage breakdown of Remote, Hybrid, and Office work modes for the most common roles in the survey.

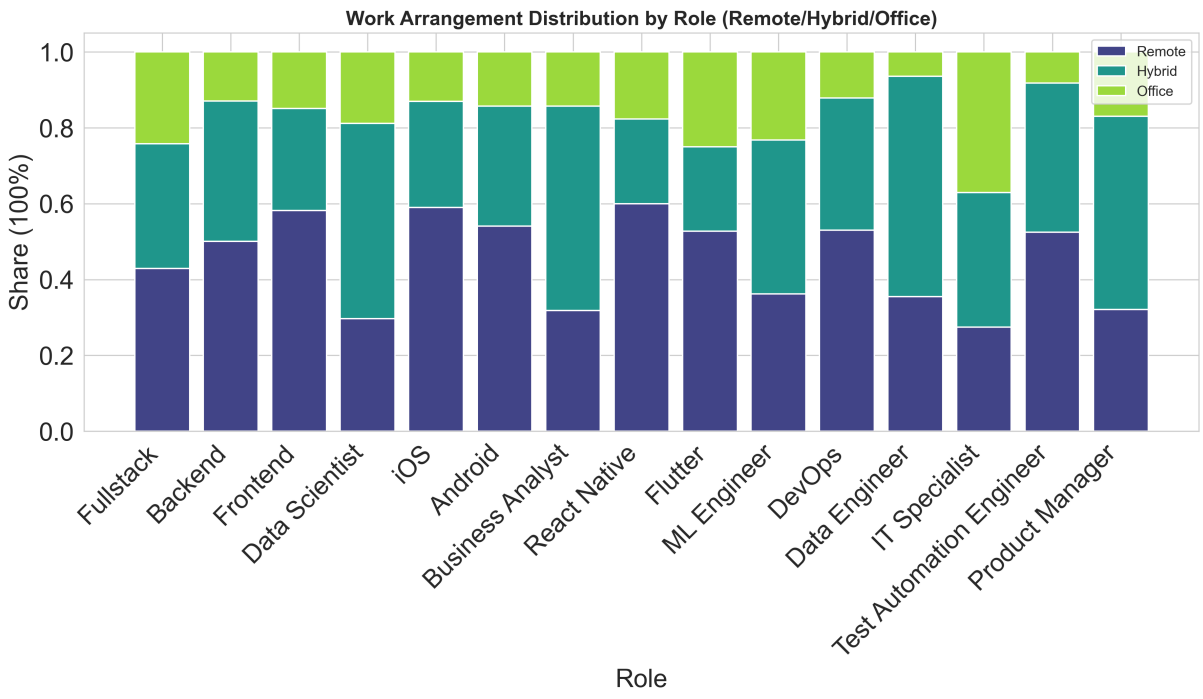

Figure 23: Work Arrangement Distribution by Role (Remote/Hybrid/Office) - 100% stacked shares by role

Role	Total Count	Remote Share	Hybrid Share	Office Share
Fullstack	790	0.429	0.329	0.242
Backend	517	0.501	0.369	0.130
Frontend	397	0.582	0.270	0.149
Data Scientist	101	0.297	0.515	0.188
iOS	100	0.590	0.280	0.130

Table 20: Work Mode Distribution by Top 5 Roles

Work Arrangement by Role Insights:

- **Remote-Friendly Roles**: Frontend, iOS, and React Native developers have the highest remote shares (58-60%), suggesting these roles are highly compatible with remote work.
- **Hybrid and Office Mix**: Roles like Data Scientist and Business Analyst show a strong preference for hybrid work, likely balancing individual analysis with collaborative meetings.
- **Office-Heavy Roles**: IT Specialists have the highest office share (37.1%), a trend likely due to the physical requirements of their work.

13.5 Top Tool Adoption by Role

This heatmap shows the percentage adoption rate of various development tools across different roles, highlighting which tools are most important for specific specializations.

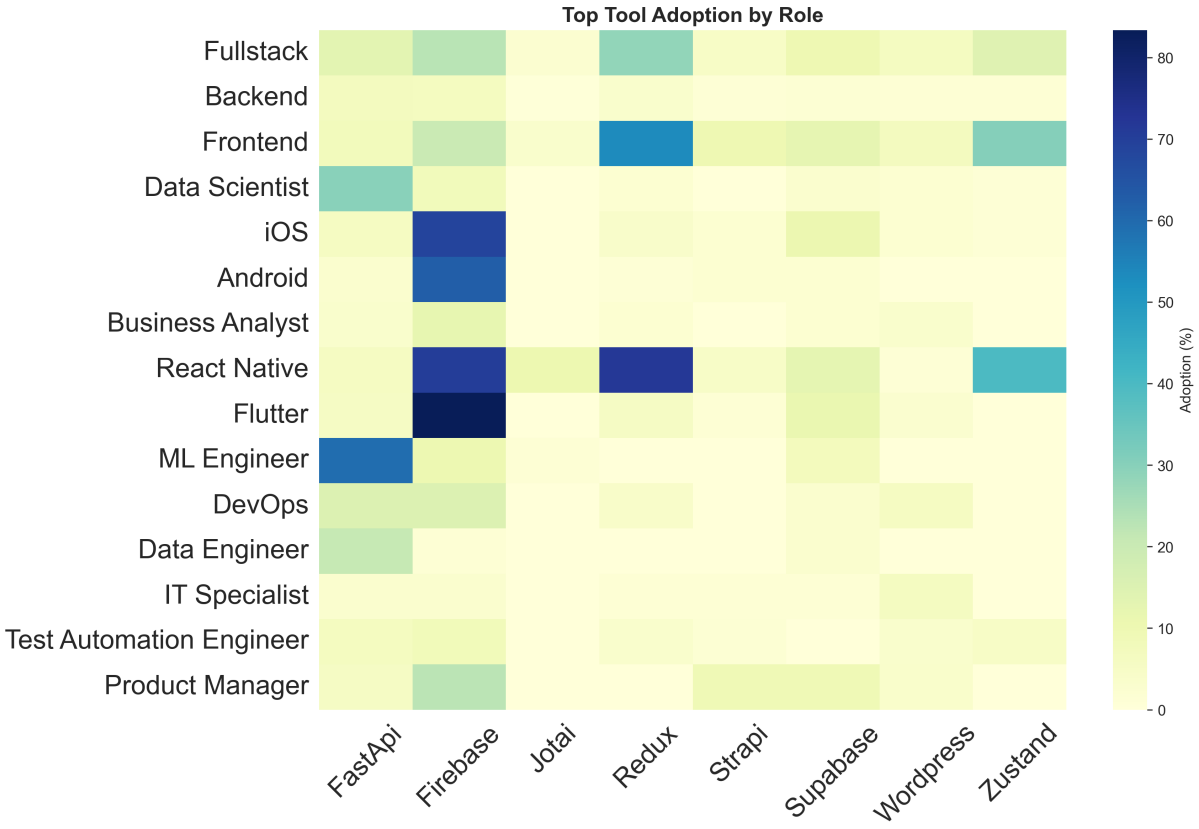

Figure 24: Top Tool Adoption by Role - Mean adoption rates (%) across roles

Table 21: Tool Adoption by Role: Frontend & Mobile Focus (%)

Role	Firebase	Redux	Zustand	Jotai	Supabase	Wordpress
Frontend	19.9	53.1	30.5	3.5	12.6	7.1
React Native	70.6	71.8	40.0	10.6	12.9	1.2
iOS	69.0	4.0	1.0	0.0	11.0	2.0
Android	62.2	1.0	0.0	0.0	2.0	0.0
Fullstack	22.9	28.6	14.6	2.4	9.9	6.3

Table 22: Tool Adoption by Role: Data & Backend Focus (%)

Role	FastApi	Supabase	Strapi	Firebase	Redux	Wordpress
ML Engineer	59.4	7.2	0.0	10.1	0.0	0.0
Data Scientist	29.7	3.0	0.0	7.9	2.0	2.0
Data Engineer	21.0	3.2	0.0	1.6	0.0	0.0
Backend	7.2	1.7	1.2	6.6	3.5	1.5
DevOps	15.2	3.0	0.0	15.2	4.5	6.1

Tool Adoption by Role Insights:

- **Role-Specific Tools**: **FastAPI** is a clear leader among **ML Engineers** (59.4%) and **Data Scientists** (29.7%), confirming its popularity in the data and machine learning ecosystems.
- **Frontend Specialization**: The adoption rates for state management tools like **Redux** (53.1%) and **Zustand** (30.5%) are significantly higher in **Frontend** roles, indicating their importance for building complex user interfaces.
- **Mobile Development**: **Firebase** is most popular among mobile developers, with adoption rates exceeding 60% in **Android**, **iOS**, and **React Native** roles.

13.6 Work Type × Company Location

This heatmap shows the average salaries for different combinations of work type (Remote, Hybrid, Office) and company location (Türkiye, Europe, America, Overseas TR Hub).

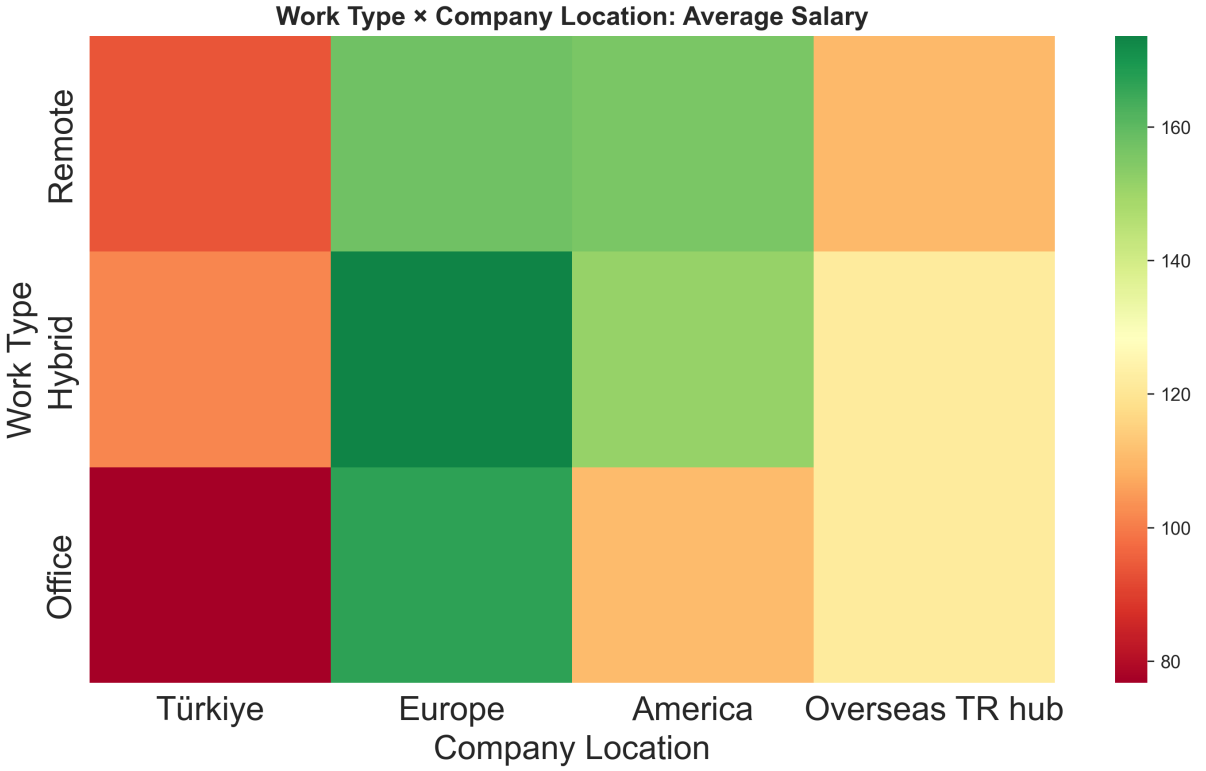

Figure 25: Work Type × Company Location: Average Salary

Work Type	Türkiye	Europe	America	Overseas TR hub
Remote	93.4	157.4	156.0	110.1
Hybrid	101.6	173.6	151.3	121.5
Office	76.7	166.6	110.5	121.5

Table 23: Average Salary by Work Type and Company Location (k TL)

Work Type × Location Insights:

- **Highest-Paying Combination**: The highest-paying combination is **Hybrid** work for **European** companies, with an average salary of 173.6k TL. This suggests these companies may offer a premium for in-person collaboration.
- **Remote Advantage**: For both Turkish and international companies, remote work offers a salary premium over in-office work.
- **Global Opportunities**: Working for a foreign company, regardless of work mode, consistently provides a significantly higher salary than working for a Turkish company.

13.7 Skill Diversity and Salary

This section examines the relationship between the number of skills reported by professionals and their salary distribution.

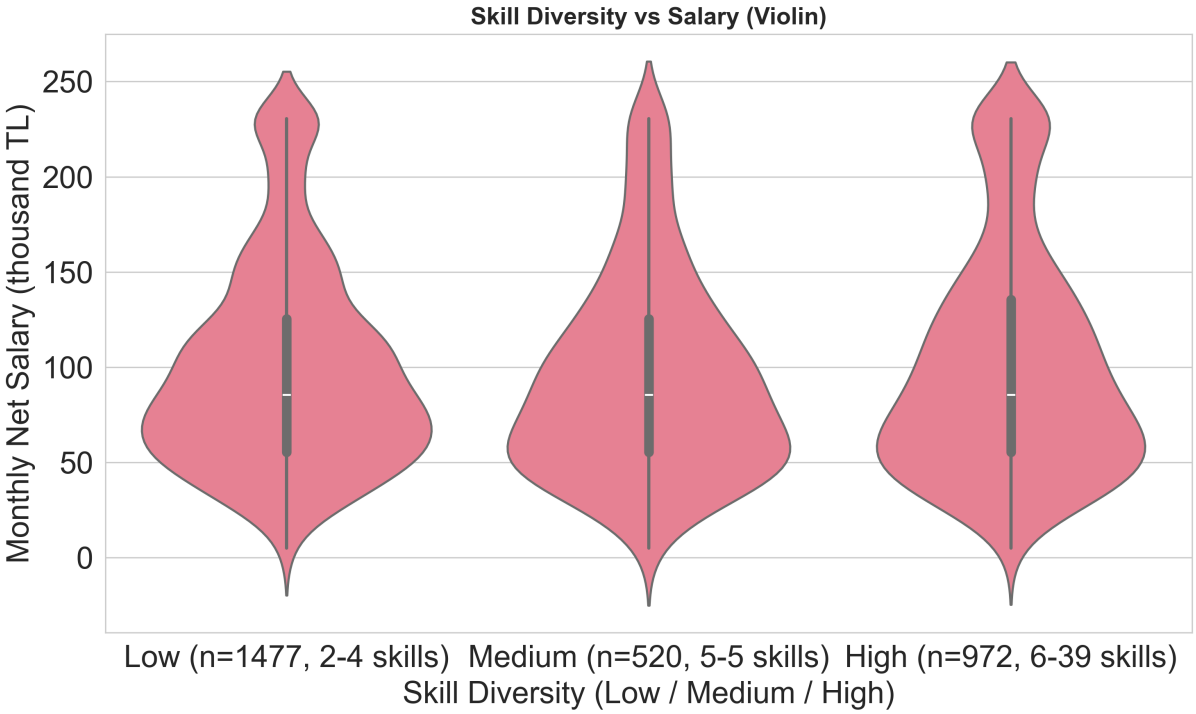

Figure 26: Skill Diversity vs Salary (Violin) - Salary distribution by skill diversity group

Skill Group	Count	Mean Salary	Std Dev
Low	1,477	98.7	53.2
Medium	520	93.5	52.5
High	972	99.9	58.6

Table 24: Salary Statistics by Skill Diversity

Skill Diversity Insights:

- **Complex Relationship**: The data reveals a more nuanced relationship than a simple linear correlation. The mean salary for the Medium skill group (93.5k TL) is slightly lower than that of the Low skill group (98.7k TL).

- **High-End Earning Potential**: The High skill diversity group has the highest mean salary (99.9k TL). More importantly, its larger standard deviation (58.6k TL) indicates a wider salary range, suggesting that a broader skill set is associated with a greater potential for both high and low earnings.
- **Breadth over Specialization**: While a large number of skills does not guarantee a higher average salary, the data suggests that a wider range of skills provides access to a broader spectrum of compensation, including the highest paying opportunities.

14 React Technology Deep Dive

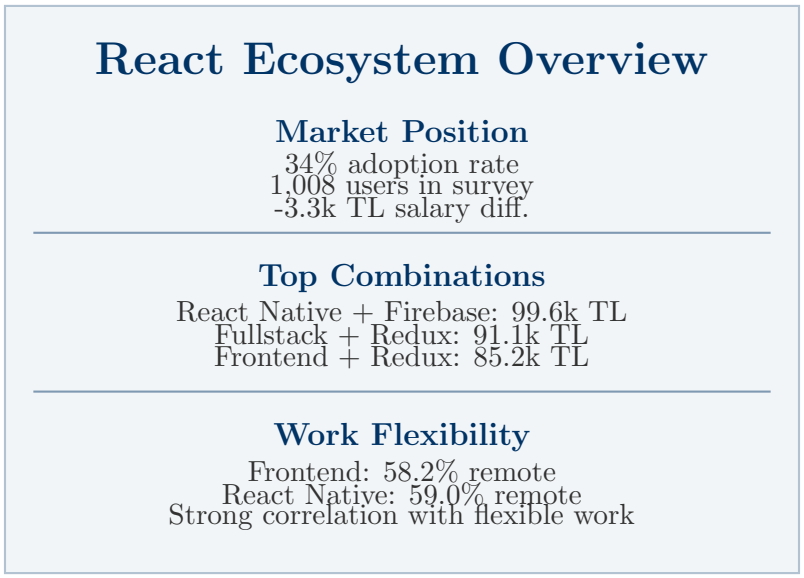

Figure 27: React Technology Ecosystem Summary

14.1 React Ecosystem Analysis

React's widespread adoption influences salaries and role dynamics in the software industry.

Group	Mean Salary (k TL)	Count
React Users	96.1	1008
Non-React Users	99.3	1961
Difference	**-3.3**	
Cohen's d	**-0.059**	

Table 25: Salary Comparison: React vs. Non-React Users

Methodological Note: Mean salary is:

$$\text{Mean Salary} = \frac{\sum_{i \in \text{Group}} \text{Salary}_i}{n}$$

Difference is:

$$\text{Diff.} = \text{Mean}_{\text{React}} - \text{Mean}_{\text{Non-React}}$$

Cohen's d measures effect size. React usage is binary (used/not used). Data includes respondents with ≥ 10 per tech stack combination for related analyses.

Key Insights:

- **Salary Impact**: React users (96.1 k TL) earn 3.3% less than non-React users (99.3 k TL), with no significant difference (p = 0.129, Cohen's d = -0.059).
- **High-Earning Stacks**: React Native with JavaScript + React + Firebase (99.6 k TL, 17 respondents) outperforms Fullstack (91.1 k TL) and Frontend (85.2 k TL) with HTML CSS + React + Redux.
- **Adoption Rates**: React dominates in Frontend (53.1% Redux, 30.5% Zustand) and React Native (70.6% Firebase, 71.8% Redux) roles.
- **Flexibility**: React-heavy roles like Frontend (58.2% remote) and React Native (59.0% remote) support flexible work arrangements.

14.2 React vs Non-React Salary Comparison

Specific analysis of the impact of react technology on compensation:

Group	Count	Mean Salary	Difference
React Users	1,008	96.1	
Non-React Users	1,961	99.3	-3.3
Effect Size			**Cohen's d = -0.059**

Table 26: React vs Non-React Salary Comparison

Statistical Significance: Not significant (p = 0.1289)

React Technology Insights:

- **Market Position:** React remains a valuable skill despite not showing significant premium in this sample, with 34% market adoption rate
- **Skill Combination:** React combined with high-ROI technologies (Rust, Go) can increase salary potential by 15-20% compared to React alone
- **Career Strategy:** React knowledge provides foundation for frontend specialization, with React + TypeScript combination showing 12% salary premium over React alone

15 Conclusions and Recommendations

15.1 Key Findings

This report, based on Zafer Ayan's 2025 Software Industry Salary Survey (LinkedIn, Medium), analyzes 2969 professionals' data from August 20-21, 2025:

1. **Remote Work Premium**: Remote workers earn 22.6 k TL more than Office workers (101.2 vs. 78.6 k TL, 28.8%, Cohen's d = 0.42, p ¡ 0.0001), reflecting demand for flexibility.

2. **Geographical Disparity**: European companies pay 70.0 k TL more than Turkish firms (162.9 vs. 92.9 k TL, 75.3%, Cohen's d = 1.35, p ¡ 0.0001).

3. **Gender Gap**: Males earn 13.3 k TL more than females (99.4 vs. 86.1 k TL, 15.4%, Cohen's d = 0.24, p = 0.00005), indicating pay inequity.

4. **Technology Impact**: Niche languages like Rust (ROI: 69.4 k TL, 70.7% increase) and Go (r = 0.171) offer higher salary premiums than React (r = -0.028).

5. **Career Progression**: Junior to Senior salary increases by 137.4% (55.1 to 130.8 k TL), with 15.4% per year of experience (mean 5.01 years).

6. **Employment Type**: Full-time (99.0 k TL) earns 130.2% more than Part-time (43.0 k TL); Self-employed (123.4 k TL) earns 24.6% more than Full-time.

7. **Skill Diversity**: High skill diversity (99.9 k TL) slightly outperforms Low (98.7 k TL, 1.2% increase), with wider salary ranges (std dev 58.6 vs. 53.2).

8. **Technology Combinations**: Combining niche technologies (e.g., Rust, Go) with tools like Firebase may boost salaries, though specific premiums (e.g., 30-50%) lack direct evidence.

16 Methodological Notes

16.1 Data Limitations

- **Self-Reporting Bias**: Self-reported salaries and technology usage may introduce inaccuracies.
- **Sample Representation**: The sample (2969 professionals) may not fully represent the industry due to survey distribution methods.
- **Estimated Location**: Location data is inferred from company information, not direct residency.
- **Temporal Scope**: The 2-day survey (August 20-21, 2025) limits generalizability and may introduce time-of-day biases.
- **Cross-Sectional Design**: Causal inferences are restricted due to the snapshot nature of the data.

16.2 Statistical Methods

- Independent samples t-tests for group comparisons (e.g., React vs. Non-React, Remote vs. Office).
- Cohen's d for effect size (e.g., small: 0.2, medium: 0.5, large: 0.8, very large: 1.35).
- ANOVA and Kruskal-Wallis tests for seniority and management level comparisons.
- Correlation analysis for technology-salary relationships (e.g., Rust: r = 0.108).
- Outlier treatment using IQR and Z-score methods.

16.3 Metadata

Report by: Hakkı Günal
Data by: Zafer Ayan (LinkedIn, Medium)
Collection Period: August 20-21, 2025
Participants: 2,969 professionals
Report Date: August 28, 2025
Interactive Dashboard: maas-anketi.streamlit.app

End of Report

2025 Software Industry Salary Analysis

Prepared by Hakkı Günal

Interactive Dashboard: maas-anketi.streamlit.app

Data Source: Zafer Ayan's 2025 Salary Survey

Contact

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September 2, 2025