Inclusion unlocks the creative potential of gender diversity in teams

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Several studies have highlighted the potential contribution of gender diversity to creativity, also noted challenges stemming from conflicts and a deficit of trust. Thus, we argue that gender diversity requires inclusion as well to see increased collective creativity. We analyzed teams in 4011 video game projects, recording weighted network data from past collaborations. We developed four measures of inclusion, based on de-segregation, strong ties across genders, and the incorporation of women into the core of the team's network. We measured creativity by the distinctiveness of game features compared to prior games. Our results show that gender diversity without inclusion does not contribute to creativity, while at maximal inclusion one standard deviation change in diversity results in .04–.09 standard deviation increase in creativity. On the flipside, at maximal inclusion but low diversity (when there is a 'token' female team member highly integrated in a male network) we see a negative impact on creativity. Considering the history of game projects in a developer firm, we see that adding diversity first, and developing inclusion later can lead to higher diversity and inclusion, compared to the alternative of recruiting developers with already existing cross-gender ties. This suggests that developer firms should encourage building inclusive collaboration ties in-house.

Groups with diverse members can be engines of creativity. Project teams—small collectives recruited for a defined task—are often used in creative fields, where nonroutine solutions are needed to solve problems¹,², and such teams boost returns to resources in innovative organizations³,⁴. There is evidence that teams possess collective intelligence beyond the mean or maximal individual intelligence of team members⁵. It is also often demonstrated, that the collective intelligence and the creative capacity of teams is a function of their cognitive diversity⁶. When team members come from diverse demographic backgrounds and have diverse past experiences, they have a higher openness to divergent thinking⁷, and they are more willing to constructively challenge the status quo⁸.

Gender diversity specifically has been shown to boost collective intelligence⁵,⁶, and the low proportion of non-dominant genders dampens innovative potential in teams¹⁰,¹¹. Women, transgender, and gender-nonconforming people (TGNC) are under-represented in STEM fields—especially in computer science and software careers¹²,¹³, and even if they embark on a career in technology, they are less appreciated and successful, and are more likely to leave at various key stages compared to men¹⁵,¹⁶. Thus it is important to analyze gender diversity in STEM teams to understand how diversity contributes to innovation when females are in minority, and often face discrimination¹⁷.

Despite a general agreement about the promise of diversity for creativity, studies on how team diversity leads to increased team performance has not reached a clear consensus¹⁸,¹⁹. It is clear that group creativity is not a simple function of individual creativity, but a complex interplay of compositional diversity, internal team structures, and the organizational-cultural environment of the team²⁰,²¹. On one hand diversity itself—while contributing to openness to creative solutions—can contribute to weakened team cohesion, and heightened conflict²². On the other hand, the right routines and communication structures within the team can multiply the power of diversity for innovation². Thus we need to consider diversity together with inclusion to understand the potential of diversity for collective creativity²³.

Others have recognized the need to take inclusion into account in understanding collective creativity²⁴–²⁶, suggesting that diversity without inclusion can lead to mistrust and a breakdown of communications²⁷, preventing a true dialog where diverse approaches to the problem at hand can be explored²⁸,²⁹. It had also been shown that the mere increase in the proportion of women in a field will not eliminate their discrimination and...
When diverse teams are well integrated, even if diversity results in conflicts, such conflicts can be beneficial to performance in complex, non-routine tasks. Following these studies, we argue that in teams with a discriminated minority—the case with gender in STEM—, without inclusion diversity will not have a positive impact on collective creativity, as various perspectives that diverse participants bring to the team would not have a chance to be contrasted and utilized.

**Gender diversity and collaboration in video game development.** Video game development is by far the largest entertainment industry today, as it overlooks movies and music in terms of gross revenues in 2003, and, by 2009, it became larger than movies and music combined. Video game development is a field that prizes creativity and distinctiveness, but it is a male-dominated field, where only about 17% of developers were female in 2010, and about 20% of them were female today. The typical content of video games is also decidedly male, as only about 13% of all characters depicted in video games are female. Video game content often encodes gender stereotypes and role expectations. Gender inequalities have been demonstrated to influence how players achieve and experience success. Such fields with low proportion of female participants also suffer from strong prejudice and discrimination against women, thus if we are able to show creative advantage to gender diversity in this strongly male dominated field, it would serve as a strong evidence for the power of gender diversity.

We analyze teams in the video game industry from 1994 to 2009. While there is a rich literature on how team composition and network ties influence performance in gameplay, we focus on team composition of developers creating games. We collected data about 8617 unique video games, relying on a website that catalogues video games via crowdsourcing and covers over 230,000 games from more than 60 countries. We also record each game’s developer studio, publishing house, market where it is available, and the year of the first release. We added data on global sales in thousands of units sold from https://vgchartz.com. For our analysis we only considered games which were published between 1993 and 2009, and had less than 2000 connection among team members, had at least one female team member, and less than 50% of team members gender could have been inferred. We excluded all re-released and mobile games. Our resulting database contains 4,011 video games. (For more details on filtering our database see Tables S1, S2 in Supplementary Information.)

Since our database goes back to the very beginnings of the video game industry, we can infer every developer’s full career path, by connecting disambiguated developer IDs with the IDs of games they had worked on in a consecutive order. We measure weighted collaborative ties between developers as the number of prior joint participations in game development projects, following others who have analyzed collaboration in co-authorship, movies, musicals, video game development, or jazz music. These approaches take a bipartite graph of person-to-event affiliations (affiliations to papers published, movies, games, or albums released), and analyze the person-to-person projection, an undirected weighted graph, where $w_{ij} = \sum_{k} a_{ik}a_{jk}$, if k is a shared affiliation for i and j at time $t-1$ that predates time $t$ of the focal event analyzed. While we follow widespread practice by defining our weighted collaboration network, we also acknowledge that there are several relevant dimensions of collaboration (for example, communication ties, collaborations outsize our game dataset, or social ties among developers) that we do not have data about.

**Measuring inclusion.** Inclusion in a work-team context can be defined as actively engaging with team members across differences: inclusion means connecting in a way such that diversity becomes a resource, rather than merely being a challenge. We cannot speak of inclusion, when differing team members are excluded from meaningful contact and collaboration, either by isolating individuals that are seen to be different, or allowing the team to fragment into homophilous subgroups. Inclusion is also absent when team members are fully assimilated, such that by connecting to others their diversity becomes muted and irrelevant in collaborations.

There is no consensus about how inclusion should be measured. A wide range of measures were proposed, that include dimensions of individual or group experiences, leadership, norms and values, influence on decisions, and access to resources, a sense of belonging, and authenticity, organizational support, and tolerance towards uniqueness. These measures require reactive data collection techniques (like surveys or interview methods), and are not scalable to large observational data.

In this article we focus on the relational aspects of inclusion, and we rely on weighted graph measures of how well gender minority members in the team are connected into the collaboration network, as evidenced by past projects. We build on past research that developed related measures conceptualized as network heterogeneity, or the co-presence of incumbency and network diversity. We develop a range of measures for inclusion, from a minimal level—lack of segregation along gender—to a stronger level—the presence of gender minority in the network core of the team.

We define three dimensions of inclusion, Fig. 1 illustrates these measures examples of weighted collaboration graphs, where the number of nodes and the proportion of genders are kept constant. Our first measure of inclusion is *mixing*: the lack of segmentation by attributes in the team. If team members are segregated, the team cannot benefit from exchanges across gender lines. Limiting collaborative connections that would allow for negotiating diverse perspectives, essential for innovation. When gender underlie subgroup formation, team identity erodes, and the salience of gender identity increases often to the extent of gender conflict. Network fragmentation along attributes can be measured by assortativity, the over-representation of ties within categories.

Our second measure of inclusion is *bonding*, that captures the strength of ties across gender categories. Strong ties are seen to be vehicles of trust, and they offer high-bandwidth interpersonal channels that are crucial in...
innovative contexts, when the information environment is complex, and updates frequently. The stronger the ties in mixed gender dyads, the broader the social bandwidth a team can rely on to develop novel solutions.

Our third measure of inclusion is incorporating: the proportion of female team members in the core of the team's network. Being in the core opens access to informal leadership, and thus offers the opportunity for women to have a say in decision making. Women in leadership positions tend to encourage participation, and facilitate broader information sharing and encourage innovation and risk-taking. Our measure of combined inclusion is then the product of the three raw measures, representing co-occurrence of various forms of inclusion. (See Quantitative Measures in Materials and Methods for formulas of inclusion metrics.)

Measuring creativity and diversity. We adopt a creativity measure—distinctiveness—defined for the video game context, which captures how unique the combination of stylistic elements was for a given game. For each game we record the presence or absence of 105 stylistic elements (recording features of perspective, gameplay, genre, or sound). We then compare games by the uniqueness of their combination of elements. The measure compares the combination of stylistic elements of a focal game to all games released in the preceding time window, using cosine distance, where a high distance indicates a game that included a unique combination of features. (We tested the robustness of the results with 1, 3, 5, and 7 year windows, and with conceptually similar novelty metrics, and present findings with five year window in the main text following.) Gender diversity is quantified by Blau's Heterogeneity Index, which reaches its maximum, 1, when the proportion of genders are equal (50% in this case) and has a minimum of 0 when the team is composed of only one gender. (See Quantitative Measures in Materials and Methods for formulas.)

Results
Predicting distinctiveness by diversity and inclusion. Gender diversity in video game development is low, albeit increasing, while there is no increase in inclusion. The proportion of female game developers is 0.15 across all teams in our dataset: less than the proportion of females in STEM and computer programming, that is around 20%. (See Gender Inferring in Materials and Methods.) As shown on Fig. 2 panel a, the female

![Figure 1. Illustrations of low and high inclusion along our three measures.](image)

![Figure 2. Gender Diversity, Inclusion and Distinctiveness over time. Solid lines indicate the mean with a 95% CI. Dashed lines show OLS trendlines. Panel a: Diversity measured by the mean proportion of female developers within game projects, and it is measured on the full sample (8617 games). Panel b: Mean combined inclusion within game projects, measured on the sample of games with at least one female developer (4011 games). Panel c: Mean distinctiveness (compared to games in the preceding 5 year window) within game projects.](image)
The proportion of game developers had been slowly increasing from 0.12 in 1994 to 0.18 in 2009. There is no comparable increase in inclusion (as shown on Fig. 2 panel b), as the combined inclusion index hovers around a mean of 0.06 without a significant trend. Considering trends in creativity (game distinctiveness), we see an early peak in 1996, and a subsequent downward trend, as industry practices and conventions solidify (see Fig. 2, panel c). However, the overall level of creativity is quite high.

We predict distinctiveness by diversity and inclusion via LOESS and OLS regression models where the unit of analysis is a game. We ran separate models for each inclusion. In each full model we controlled for multiple variables representing potential alternative explanations for the association between diversity × inclusion and distinctiveness: Team size is measured as the number of team members involved in the game production. Larger teams are typically assembled by more established developer firms, therefore more likely to have bigger networks and employ more women, and also have more leeway to experiment with novel game ideas. Ratio of center measures the proportion of developers in the team network who belong to the center. Flatter organizations (with a larger center) are also more likely to have women in the center just by chance, while they are also likely to be more creative. Number of Newbies measures the number of team members with no prior experience in game development (based on our database). Newbies might bring novel ideas to the team, but we have no data on their level of inclusion. We also recorded the Number of star developers, those who have received a Game Developers Choice Award. Awardees are typically male and can afford to develop more distinctive games. Game tenure captures the experience level of a team, measured as the average number of games team members have produced prior to the year of production of the given game. Single-Firm Production is a dummy variable, which is 1 if the publisher and the developer company is the same entity, otherwise 0. Such integrated companies could make a more immediate connection between game design and consumer preferences, moving faster to distinctive solutions. We controlled for the platforms the game was developed for, because certain genres and platforms can be more popular than others—both with consumers and developers. We also controlled for temporal trends, with the 1 year of release and the number of countries the game was released at.

As expected by the literature, we find that gender diversity is positively related to creativity in video game projects, even without considering inclusion. Considering games as units of analysis, one standard deviation increase in gender diversity results in 0.09 (95% CI 0.06; 0.12) standard deviation increase in creativity (as shown on Fig. 3 Panel b).

We found a positive overall relationship between distinctiveness and the interaction (product) of diversity and inclusion, as the LOESS curves show on Fig. 3 Panel a. Taking control variables into account in OLS models, Fig. 3. Panel b. shows points estimates of standardized gender diversity, forms of inclusion, and the interaction of gender diversity and inclusion. Our results hold if different robustness checks are applied (1) distinctiveness is calculated on different time windows (1, 3, 7), (2) creativity is conceptualized as novelty followed by evolutionary, and (3) if models are applied on different subsets of database suggested by. (See Creativity Prediction Model Tables in SI Tables S4–S27., and Prediction Results on SI Figs. S5 and S6.)

We found that once we take inclusion into account, gender diversity without inclusion does not contribute to group creativity. We also found that inclusion without diversity (with the minimal diversity possible) does not contribute to group creativity. The main effect of inclusion is mostly negative: two of our three measures (mixing and bonding) show significant negative coefficients (mixing: −0.07, 95% CI −0.12; −0.01; bonding: −0.13, 95% CI −0.21; −0.06). Our results hold if we control for developer firm level heterogeneity (with random or fixed

**Figure 3.** Distinctiveness as a function of the interaction of diversity and inclusion. Panel a: LOESS estimates of distinctiveness by the product of diversity and three measures of inclusion with 95% CI; separate lines are shown with abbreviated labels for diversity × mixing, diversity × bonding, and diversity × incorporating. Panel b: OLS point estimates with clustered standard errors for developer firm of standardized distinctiveness with 95% CI, for: gender diversity, variables of inclusion, and their interactions with gender diversity. Markers are numbered according to OLS models; coefficients represent one SD change in distinctiveness as a result of one SD change in independent variables. Point estimate for the main effect of gender diversity without entering inclusion is shown as Model 0, in red. Non-significant estimates at p < .05 are shown in gray. Panel c: Predicted distinctiveness by gender diversity at minimal and maximal levels of Mixing Inclusion with 95% CI, keeping all controls at their means. The figure shows model predictions for synthetic data, where we can compare the predicted distinctiveness of synthetic game projects as we manipulate diversity, and keep inclusion either at the minimum (0) or at the maximum (1)
effects for developer firm intercepts), or when we aggregate the data to the developer firm level. (See firm-level point estimates in Fig. S2, panel d in Supplementary Information.)

These estimates indicate that inclusion without gender diversity does not help creativity. Of course, inclusion is not interpretable for zero diversity; these estimates indicate that increasing inclusion at minimal levels of diversity will not help creativity. It is likely that high inclusion at low levels of diversity leads to assimilation and tokenism that was previously shown to nullify creative benefits to diversity.47

Creativity in game development benefits from gender diversity with inclusion only. Game developer teams should include female collaborators, and also integrate them with the rest of the team to see a boost in creativity. We turn to analyze histories of game developer firms, to understand if intervention in diversity, or intervention in inclusion is the more promising avenue to overcome barriers in developer firms. In the first case, if boosting diversity is the key to advancing both diversity and inclusion, firms can add female developers to their teams, and then subsequently see an increase in inclusion, when female developers build ties to male developers in repeated game projects. In the second case, if firms can intervene by adding inclusion, the key is to hire subsets of developers with gender diversity and pre-existing ties between female and male team members. In this case, inclusion is not “home grown”, but rather a function of clustered migration of developers among firms. This process was recently described as the "trojan horse" mechanism, driven by a sequence of clustered migration of individuals who have prior collaborative ties between them.

To capture the primary drivers of firm-level processes, we use transfer entropy, a measure that captures the amount of information that values in one time series have about subsequent values of another time series.68,69

We measure transfer entropy between two processes: the developer firm-level times series of diversity and inclusion, in both directions. We enter the resulting variables, transfer entropy $T_{D \rightarrow I}$ and $T_{I \rightarrow D}$ in an OLS model that predicts the final diversity and inclusion (the last values in time that we see for a given firm in our dataset), and the trends of diversity and inclusion at the developer firm level. Figure 4 Panels a and b show two examples, the one Panel a where inclusion predicts diversity the most, and a second on Panel b where diversity predicts inclusion the most.

Figure 4 Panel c shows point estimates predicting firm-level diversity and inclusion. We found that boosting diversity and inclusion seems to be a product of a diversity-driven process, where changes in diversity result in changes in inclusion. This process in practice can be conceptualized as the hiring of female developers regardless of their prior histories of collaboration with other team members, and subsequently adding inclusion by facilitating repeated collaborations between female and male developers—a form of “home grown” inclusion. The reverse direction of temporal influence between processes does not seem to lead to increased diversity or inclusion: When firms add inclusion first (and diversity is a result of this subsequently), we should expect no measurable advantage in increased diversity or inclusion. In practice such a process would mean hiring dyads of female and male developers with pre-existing collaboration ties, which we could label as “acquired inclusion”.

This indicates that developer firms should not hesitate to add novice female developers to their teams—even if they cannot expect immediate creativity benefits in the team with female developers without inclusion, as female developers would not yet have cross-gender collaborative ties. Female developers will accumulate collaborative ties, and thus achieve inclusion subsequently, and the team can expect to see a boost in creativity.

Discussion

As others have already found, we have also shown that gender diversity is a predictor of creativity.8,11,63, adding females to a team in a male-dominated industry like video game development contributes to the distinctiveness of the final product. However, it is not enough to add female developers to a team, but female team members should
While there is a positive link between gender diversity × inclusion, and distinctiveness, this does not translate into a positive link between gender diversity × inclusion and success. (See Diversity, inclusion, and forms of advantage).

This selectivity seems to prevent games made with higher gender diversity from reaching higher review scores. Games made with higher gender diversity face a higher probability of being ignored (not being reviewed at all). This delayed onset of benefits is likely a contributor to the sustained marginalization of female developers in the field, reinforcing beliefs in the benefits of male-skewed (or all-male) team composition. Second, even if a video game developer firm is successful in achieving higher creativity via diverse metrics that all support the same conclusion: gender diversity without inclusion does not lead to benefits in creativity.

At the same time, we also see evidence that tokenism—the minimal presence of a gender minority—is not effective. When an all-male team adds one female member only, the team can expect no creativity benefits. In fact, when we observe developer firms with exclusively male teams in their history adding a female developer for the first time, there is a slight decrease in creativity. Our findings underscore prior findings about the limits of tokenism: when gender diversity is low, inclusion acts more as assimilation that possibly silences the creative potential in diversity. One female team member closely linked with others in the team will not be able to voice and represent a diverse perspective in a male-dominated industry.

Our results point to several reasons why organizations would face difficulties increasing gender diversity. First, as a developer firm would be looking to increase diversity from zero, or very low levels, it would not see early benefits in increased creativity. Organizations need to add and also include in their collaborative network a relatively high proportion of female developers (about 23%—significantly higher than the industry average of 19%) to start seeing creativity benefits. This delayed onset of benefits is likely a contributor to the sustained marginalization of female developers in the field, reinforcing beliefs in the benefits of male-skewed (or all-male) team composition. Second, even if a video game developer firm is successful in achieving higher creativity via diversity and inclusion, the payoffs in terms of success will be hampered by gatekeepers that review video games, which are biased against games made with higher gender diversity from reaching higher review scores. This selectivity seems to prevent games made with higher gender diversity from reaching higher review scores. While there is a positive link between gender diversity × inclusion, and distinctiveness, this does not translate into a positive link between gender diversity × inclusion and success. (See Diversity, inclusion, and forms of success in SI Fig. S8).

Games made with higher female participation are disadvantaged in reviews: the probability that a game will be reviewed at all, sharply declines as the proportion of female developers increases. It seems that reviewing is a male-dominated activity, that can possibly lead to a dis-preference towards games made with higher female participation, as the named list of developers is also visible to reviewers. (See the name and the inferred gender of publicly available employees including game reviewers at Kotaku, Gameinformer and Eurogamer at SI Table 29–31) Beyond being disadvantaged in the chances to get a review, games where diversity × inclusion is higher we see a significantly lower review score, even if we keep distinctiveness and other relevant features of the team, game, and company constant. However, once we control for selection bias—the fact that review scores are not missing at random, but exclusion form reviewing is a strong function of gender diversity—we do not see a disadvantage for diversity × inclusion in term of review score. This suggests that if we can eliminate potential in diversity. One female team member closely linked with others in the team will not be able to voice and represent a diverse perspective in a male-dominated industry.
discrimination against gender diversity in the decision to review games, the creativity benefit that stems from diversity x inclusion would translate into a higher review score, hence distinctiveness is a significant positive predictor of review score. (See Heckman Selection Model and OLS model in SI Table S28.) Firms might be tempted to hire subsets of developers with diverse genders and also with prior links of inclusion already established among them—taking a wholesale approach to jump-start a diverse and inclusive creative team. However, we found evidence that it is more beneficial to take a stepwise approach: Firms should first increase diversity, and then inclusion. By our results, organizations should aim to recruit novice, unconnected female collaborators, and then increase their inclusion by employing these novice female team members in repeated projects. The alternative approach of recruiting diverse team members already with a history of cross-gender collaborations does not lead to a sustained increase in diversity and inclusion.

Limitations. Limitations of our study chiefly relate to the definition and measurement of diversity and collaboration. Gender identity is not binary, however such personal information could be only analyzed if self-claimed gender identity is provided, therefore we could not incorporate non-binary gender into this study. We are also aware of the limitations and the potential biases of name-based inferring methods, such algorithms perform better on Western-names. Therefore we inferred the name-based ethnicity of developers using an increasingly popular web solution the Ethnea api. To quantify the impact of unknown filtering we compared the ratio of developers with Western names within our final dataset, and before filtering teams out with more than 50% unknowns. We found no significant difference between the distribution of Ratio of Western origin team members (Mann–Whitney Statistics = 11,060,581.000, p = 0.482).

To account for the potential bias that the presence of unknowns within teams implies we performed robustness checks and found even if 50% of unknowns are male the positive interaction of gender diversity and inclusion persists in the case of combined index and bonding but mixing and incorporating are more sensitive to such bias. (For further details see Impact of Gender Robustness on Modelling in SI, and Figs. S4 and S5.) Our measurement of past collaboration was restricted to collaborations within the population of games in our dataset, thus we have no data about past collaborations in game projects not in the database, or projects in other industries. To fully capture inclusion, we would also need to have multiplex network data about communication and other relevant on-project relationships, as well as a subjective sense of acceptance. Our measure of diversity did not take dimensions beyond gender into account, while in collaborative settings complex intersectional diversity is at play.

Methods

Gender inferring. Similarly, to film credits, Moby Games lists each team member’s full name and task in the production (imaging, scripting, design, music, etc.). To infer team members’ gender, we relied on developers’ full names, and adopt a commonly used first-name based gender inferring method. Specifically, our method is relying on 2016 US baby game database, published by the US Social Security Administration annually. (SSA 2016). Our algorithm splits names in credit lists into first and last names, then checks whether the given first name is in our database and for which gender. Since some names are used for both males and females each name has a probability of being male based on the fraction of times when the given first name was assigned to a male baby. To be very certain of the result of the gender inferring method, we only label those as male whose probability is higher or equal to 0.9 and as female is lower or equal to 0.1. Names that have only initials, or their name is relying on 2016 US baby game database, published by the US Social Security Administration annually. (SSA 2016). Our algorithm splits names in credit lists into first and last names, then checks whether the given first name is in our database and for which gender. Since some names are used for both males and females each name has a probability of being male based on the fraction of times when the given first name was assigned to a male baby. To be very certain of the result of the gender inferring method, we only label those as male whose probability is higher or equal to 0.9 and as female is lower or equal to 0.1. Names that have only initials, or their probability is between 0.1 < p < 0.9 are labelled as unknowns. The method that we selected is optimized for high precision, where names with high probability for being unisex are labelled as unknowns. Our gender inferring yielded 19% female, 63% male and 18% unknowns. (For further details on the accuracy of gender inferring see Accuracy of Gender Inferring, Fig. S1, Table S3 in Supplementary Information.)

Quantitative measures. Dependent Variable: We measure creativity by adopting De Vann et al’s distinctiveness metric, which compares the combination of each game’s stylistic elements to all games released in the preceding 5 years and compute and average distance (1 - cosine similarity) between them. (See SI List of stylistic elements used to quantify Distinctiveness and Novelty) Since we do not know the exact publish date of a very game, we did not compare games published within the same to avoid temporal aversion.

Cosine Distance $d_{ij}$ is calculated (1) by comparing the vectors of stylistic elements of all game $i$ with all other game $j$, the following:

$$d_{ij} = 1 - \frac{1}{\sqrt{\sum_{k=1}^{K} g_{ik} g_{jk} / \left( \sum_{k=1}^{K} g_{ik}^2 \right)^{1/2} \left( \sum_{k=1}^{K} g_{jk}^2 \right)^{1/2}}}$$

where $g_{ik}$ is 1/K if a given stylistic element $k$ was used in game $i$ and 0 otherwise. Then the resulting similarity is subtracted from 1. (2) Finally we normalize these game-pair distances for all games (1, 2, ..., j) published in the proceeding 5 years, as the following:

$$Creativity = \frac{1}{N} \sum_{j=1,j\neq i}^{N} d_{ij}$$

Independent Variables—Gender Diversity and Team cohesion metrics.
**Gender Diversity: Blau’s index.** We use Blau’s Heterogeneity Index as our measure of diversity. It is calculated as 
\[ H_B = 1 - \sum P_i^2, \]
where \( P_i \) is the ratio of group members in category \( i \) (male or female). Therefore, the female-male ratio is 50–50% the Blau’s Index is 1, and when a team is composed only by one gender group is 0.

We measured inclusion in four ways by using network-based segregation metrics:

**Mixing as reversed assortativity.** Assortativity Coefficient developed by Mark Newman\(^4\) measures the similarity of connections in the graph with respect to the given attribute. It has been widely used to measure homophily in various (social) networks: such as sexual contacts and marriage matching\(^5\), demographics on Facebook\(^6\), book recommendation networks\(^7\) or the research interests of scientists who follow each other on twitter\(^8\). The Assortativity Coefficient, \( r \) is calculated as the Pearson correlation coefficient of degrees between pairs of nodes, formally \( r = \frac{\text{Tr}(M) - \sum M^2}{\sqrt{\text{Trace}(M^2) \cdot \text{Trace}(M^2) - 2 \cdot \text{Trace}(M^2)^2}} \), where \( M \) is the mixing matrix (joint probability) of the two genders, and \( \text{Tr}(M) \) is the trace (sum of elements in the diagonal) of matrix \( M \). \( r = 0 \) is where the network is perfectly disassortative, meaning that every edge connects a node to a different type, while \( r = 1 \) means perfect assortativity, when the network is fully segregated, such that nodes from type \( i \) do not connect to nodes of type \( j \). We quantify reversed assortativity by subtracting it from one and normalizing it: \( \text{Mixing} = \frac{1 - r}{\max(1 - r)} \). Large values of Mixing mean high inclusion—team members are mixed by gender, and low values indicate gender segregation.

- One of the beneficial attributes of assortativity coefficient while measuring segregation is that this metric is insensitive to the number of isolated nodes within the network\(^9\). Because our collaboration networks are based on previous shared collaborations we have a higher number of isolated group members, which we should not consider while analyzing the network structure.

**Bonding as the ratio of weighted cross-gender ties.** More frequent shared project experience indicates more intense relationship among team members, which can be a proxy for higher inclusion. Women have been shown to strive and feel more included in workplaces where they could develop stronger ties\(^10\). Stronger ties were also shown to be beneficial to transfer complex knowledge\(^11,12\) and solve complex problems\(^13\). Therefore, our second metric quantifies gendered inclusion as the total number of times men and women worked together in previously divided by the total number of shared working experience of team: \( \text{Bonding} = \frac{\sum W_{FM}}{\sum W_i} \), where \( \sum W_{FM} \) is the sum of weights that connect different gender groups, and \( \sum W_i \) is the sum of all weights within the network.

**Incorporating as the ratio of women in the graph center.** Our third inclusion metric captures how central women’s position within the team network, specifically the ratio of women within the collaboration network’s center. Network center is defined as the Jordan center of a graph, which is a set of nodes where eccentricity is equal to graphs’ radius. The eccentricity \( \varepsilon(n) \) of a node \( n \) measures how far a node is from the furthest node in the graph. Formally \( \varepsilon(n) = \max(n, u) \). The radius \( r \) of a graph is the minimum eccentricity of any node, formally \( r = \min \varepsilon(n) \). To measure which team members belong to the center we used “Python 3. NetworkX Center Distance Metric.” Finally we take the natural logarithm of the ratio of women in the center to ensure a better distribution, therefore calculated as \( \text{ncorporating} = \log \left( \frac{N_{w\in C}}{N_w} \right) \), where \( N_{w\in C} \) is the number of women in the center \( N_w \) is the number of women in the network.

**Combined inclusion.** Our fourth measure of inclusion is the combination of the first three, as a product of the three measures of inclusion: mixing, bonding, and incorporating.

**Time series analysis.** We have filtered our data to include games from developer firms that had at least four games in the dataset. This resulted in a dataset with 2418 games from 308 developer firms, filtered from the original dataset of 4011 games from 1354 firms. Distributions of key variables (creativity, diversity, and combined inclusion) in the filtered dataset did not differ from the full dataset (with Kolmogorov–Smirnov test p values of 0.99, 0.65, and 0.83 respectively), and the means of these variables were not significantly different either (with Wilcoxon rank sum test p-values of 0.57, 0.22, and 0.83 respectively). We recorded the diversity and combined inclusion scores for these games, and we calculated transfer entropy from diversity to inclusion, and from inclusion to diversity as \( \text{TX} \rightarrow \text{Y} = S(Y_t|Y_{t-1} \rightarrow L) - S(Y_t|Y_{t-1} \rightarrow L, X_{t-1} \rightarrow 1 - L) \), where \( S(Y) \) is the Shannon entropy of \( Y \).

Since time resolution for the publication date for games in annual, we had several games within a developer firm that were from the same year. For these games with tied dates we have used random sorting, and re-calculated transfer entropies. We used 500 random sortings of ties for all temporal sequences. We then calculated the mean transfer entropy scores of these 500 sequences for each developer firm game sequence.

**Data availability**
Dataset used for analysis is publicly available at that link: [https://github.com/velf/moby_data](https://github.com/velf/moby_data).

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**References**
1. Amabile, T. M. The meaning and measurement of creativity. In *The Social Psychology of Creativity* 17–35 (Springer, 1983).
2. Kozlowski, S. W. J. & Bell, B. S. Work groups and teams in organizations. In *Handbook of Psychology, Volume 12: Industrial and Organizational Psychology* (eds Weiner, I. B. et al.) 412–469 (Wiley, 2013).
3. Wuchty, S., Jones, B. F. & Uzzi, B. The increasing dominance of teams in production of knowledge. *Science* **316**, 1036–1039 (2007).
9. Xie, L., Zhou, J., Zong, Q. & Lu, Q. Gender diversity in R&D teams and innovation efficiency: Role of the innovation context.

8. Amabile, T. M., Conti, R., Coon, H., Lazenby, J. & Herron, M. Assessing the work environment for creativity. *AMJ* **39**, 1154–1184 (1996).

1169–1179 (International World Wide Web Conferences Steering Committee, 2016). https://doi.org/10.1145/2872427.2883073.

11. Haverkamp, A., Bothwell, M., Montfort, D. & Driskill, Q.-L. Calling for a paradigm shift in the study of gender in engineering education. *Stud. Eng. Educ.* **1**, 55 (2021).

12. Cheryan, S., Ziegler, S. A., Montoya, A. K. & Jiang, L. Why are some STEM fields more gender balanced than others? *Psychol. Bull.* **143**, 1–35 (2017).

14. Way, S. F., Larremore, D. B. & Clauset, A. Gender, productivity, and prestige in computer science faculty hiring networks. In *Proceedings of the 25th International Conference on World Wide Web* 1169–1179 (International World Wide Web Conferences Steering Committee, 2016). https://doi.org/10.1145/2872427.2883073.

15. Clark Blickenstaff, J. Women and science careers: Leaky pipeline or gender filter?. *Gend. Educ.* **17**, 369–386 (2005).

16. Vedres, B. & Vasarhelyi, O. Gendered behavior as a disadvantage in open source software development. *EPJ Data Sci.* **8**, 25 (2019).

17. Brooke, S. "Condescending, rude, assholes": Framing gender and hostility on stack overflow. In *Proceedings of the Third Workshop on Abusive Language Online* 172–180 (Association for Computational Linguistics, 2019). https://doi.org/10.18653/v1/W19-3519.

18. Joshi, A. & Roh, H. The role of context in work team diversity research: A meta-analytic review. *Acad. Manag. J.* **52**, 599–627 (2009).

19. van Knippenberg, D., De Dreu, C. K. W. & Homan, A. C. Work group diversity and group performance: An integrative model and research agenda. *J. Appl. Psychol.* **89**, 1008–1022 (2004).

20. Vedres, B. & Stark, D. Structural folds: Generative disruption in overlapping groups. *Am. J. Sociol.* **115**, 1150–1190 (2010).

21. Woodman, R. W., Sawyer, J. E. & Griffin, R. W. Toward a theory of organizational creativity. *AMIR* **18**, 293–321 (1993).

22. Webber, S. S. & Donahue, L. M. Impact of highly and less job-related diversity on work group cohesion and performance: A meta-analysis. *AMJ* **27**, 141–162 (2001).

23. Milliken, F. J. & Martins, L. L. Searching for common threads: Understanding the multiple effects of diversity in organizational groups, *AMJ* **21**, 402–433 (1996).

24. De Dreu, C. K. W. & West, M. A. Minority dissent and team innovation: The importance of participation in decision making. *J. Appl. Psychol.* **86**, 1191–1201 (2001).

25. Ferdman, B. M. Diversity at work: The practice of inclusion. (Jossey-Bass, A Wiley Brand, 2014)

26. Mor Barak, M. E. & Cherin, D. A tool to expand organizational understanding of workforce diversity: Exploring a measure of inclusion-exclusion. *Adm. Soc. Work* **22**, 47–64 (1998).

27. Jansen, W. S., Otten, S., van der Zee, K. I. & Jans, L. Inclusion: Conceptualization and measurement: Inclusion: Conceptualization and measurement. *Eur. J. Soc. Psychol.* **44**, 370–385 (2014).

28. Kooistra, J. Newzoo's trends to watch in 2019. https://newzoo.com/insights/articles/newzoo's-trends-to-watch-in-2019/ (2019).

29. de Vaan, M., Vedres, B. & Stark, D. The topology of creativity. *EPJ Data Sci.* **7**, 615–631 (1996).

30. Nishii, L. H. & Gonzcalo, J. A. Demographic faultlines and creativity in diverse groups. In *Calling for a Paradigm Shift in the Study of Gender in Engineering Education*, pp. 1–11 (McGraw-Hill Education, 2013).

31. Tschang, F. T. Balancing the tensions between rationalization and creativity in the video games industry. *Organ. Sci.* **18**, 989–1005 (2007).

32. de Vaan, M., Vedres, B. & Stark, D. Game changer: The topology of creativity in video games. *Organ. Sci.* **18**, 815–834 (2009).

33. Austin, J. “I suppose I’ll be patching you up, as usual”: Women’s roles and normative femininity in a team-based video game. *New Media Soc.* **24**, 1116–1132 (2022).

34. Hamlen, K. R. Re-examining gender differences in video game play: Time spent and feelings of success. *J. Educ. Comput. Res.* **43**, 293–308 (2010).

35. Sapienza, A., Zeng, Y., Bessi, A., Lerman, K. & Ferrara, E. Individual performance in team-based online games. *R. Soc. Open Sci.* **5**, 180329 (2018).

36. Bailey, E. N., Miyata, K. & Yoshida, T. Gender composition of teams and studios in video game development. *Games Cult.* **16**, 42–64 (2021).

37. Williams, D., Martins, N., Consalvo, M. & Ivory, J. D. The virtual census: Representations of gender, race and age in video games. *New Media Soc.* **11**, 815–834 (2009).

38. Zeng, Y., Sapienza, A. & Ferrara, E. The influence of social ties on performance in team-based online games. *IEEE Trans. Games* **13**, 358–367 (2021).

39. Newman, M. E. J. The structure of scientific collaboration networks. *Proc. Natl. Acad. Sci.* **98**, 404–409 (2001).

40. Lutter, M. Do women suffer from network closure? The moderating effect of social capital on gender inequality in a project-based labor market, 1929 of 2010. *Am. Sociol. Rev.* **80**, 329–358 (2015).

41. Phillips, D. J. Jazz and the disconnected: City structural disconnectedness and the emergence of a Jazz Canon, 1897–1933. *Am. J. Sociol.* **117**, 420–483 (2011).

42. Wachs, J. & Vedres, B. Does crowdfunding really foster innovation? Evidence from the board game industry. *Technol. Forecast. Soc. Chang.* **168**, 120747 (2021).

43. Guimera, R., Uzzi, B., Spiro, J. & Amaral, L. A. Team assembly mechanisms determine collaboration network structure and team performance. *Science* **308**, 697–702 (2005).

44. Shore, L. M. et al. Inclusion and diversity in work groups: A review and model for future research. *J. Manag.* **37**, 1262–1289 (2011).

45. Phillips, D. J. Jazz and the disconnected: City structural disconnectedness and the emergence of a Jazz Canon, 1897–1933. *Am. J. Sociol.* **117**, 420–483 (2011).

46. Chung, B. G. et al. Work group inclusion: Test of a scale and model. *Group Organ. Manag.* **45**, 75–102 (2020).

47. Reagans, R. & Zuckerman, E. W. Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organ. Sci.* **12**, 502–517 (2001).
52. Northcraft, G. B., Polner, J. T., Neale, M. A. & Kramer, R. M. Diversity, social identity, and performance: Emergent social dynamics in cross-functional teams. In Diversity in work teams: Research paradigms for a changing workplace (eds Jackson, S. E. & Ruderman, M.) (American Psychological Association, 1995).
53. Carton, A. M. & Cummings, J. N. A theory of subgroups in work teams. AMR 37, 441–470 (2012).
54. Newman, M. E. J. Assortative mixing in networks. Phys. Rev. Lett. 89, 208701 (2002).
55. Granovetter, M. The strength of weak ties. Am. J. Sociol. 78, 1360–1380 (1973).
56. Aral, S. & Van Alstyne, M. The diversity-bandwidth trade-off. Am. J. Sociol. 117, 90–171 (2011).
57. Rosener, J. B. Ways women lead. In Leadership, gender, and organization Vol. 27 (eds Werhane, P. & Painter-Morland, M.) 19–29 (Springer, 2011).
58. Adams, R. B. & Funk, P. Beyond the glass ceiling: Does gender matter? Manag. Sci. 58, 219–235 (2012).
59. Yang, Y., Tian, T. Y., Woodruff, T. K., Jones, B. F. & Uzzi, B. Gender-diverse teams produce more novel and higher-impact scientific ideas. Proc. Natl. Acad. Sci. U.S.A. 119, e2208841119 (2022).
60. Beckhusen, J. Occupations in Information Technology (US Census Bureau, 2016).
61. United States of America. Department of Labor. Women’s Bureau (WB)—Computer and Information Technology Occupations. (2015).
62. Sawyer, R. K. Group genius: the creative power of collaboration. (Basic Books, 2007).
63. Bear, J. B. & Woolley, A. W. The role of gender in team collaboration and performance. Interdisc. Sci. Rev. 36, 146–153 (2011).
64. Brambor, T., Clark, W. R. & Golder, M. Understanding interaction models: Improving empirical analyses. Polit. Anal. 14, 63–82 (2006).
65. Greene, W. H. Econometric Analysis (Prentice Hall, 2003).
66. Killingsworth, M. A., Kahneman, D. & Mellers, B. Income and emotional well-being: A conflict resolved. Proc. Natl. Acad. Sci. U.S.A. 120, e208661120 (2023).
67. Arvidsson, M., Collet, F. & Hedström, P. The Trojan-horse mechanism: How networks reduce gender segregation. Sci. Adv. 7, eabf6730 (2021).
68. Barnett, L., Barrett, A. B. & Seth, A. K. Granger causality and transfer entropy are equivalent for gaussian variables. Phys. Rev. Lett. 103, 238701 (2009).
69. Schreiber, T. Measuring information transfer. Phys. Rev. Lett. 85, 461–464 (2000).
70. Farh, C. I. et al. Token female voice enactment in traditionally male-dominated teams: Facilitating conditions and consequences for performance. Acad. Manag. J. 63, 832–856 (2020).
71. Guldiken, O., Mallon, M. R., Fainshmidt, S., Judge, W. Q. & Clark, C. E. Beyond tokenism: How strategic leaders influence more meaningful gender diversity on boards of directors. Strateg. Manag. J. 40, 2024–2046 (2019).
72. Karimi, F., Wagner, C., Lemmerich, F., Jadidi, M. & Strohmaier, M. Inferring gender from names on the web: A comparative evaluation of gender detection methods. In Proceedings of the 25th International Conference Companion on World Wide Web—WWW ’16 Companion 53–54 (2016). https://doi.org/10.1145/2872518.2889385.
73. Torvik, V. I. & Agarwal, S. Ethnica—an instance-based ethnicity classifier based on geo-coded author names in a large-scale bibliographic database. In (2016).
74. Newman, M. E. J. Mixing patterns in networks. Phys. Rev. E 67, 026126 (2003).
75. Girvan, M. & Newman, M. E. J. Community structure in social and biological networks. Proc. Natl. Acad. Sci. 99, 7821–7826 (2002).
76. Traud, A. L., Mucha, P. J. & Porter, M. A. Social structure of Facebook networks. Physica A 391, 4165–4180 (2012).
77. Bucur, D. Gender homophily in online book networks. Inf. Sci. 481, 229–243 (2019).
78. Ke, Q., Ahn, Y.-Y. & Sugimoto, C. R. A systematic identification and analysis of scientists on Twitter. PLoS ONE 12, e0175368 (2017).
79. Bojanowski, M. & Corten, R. Measuring segregation in social networks. Soc. Netw. 39, 14–32 (2014).
80. Timberlake, S. Social capital and gender in the workplace. J. Manag. Dev. 24, 34–44 (2005).
81. Hansen, M. T. The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. Adm. Sci. Q. 44, 82–111 (1999).
82. Nahapiet, J. & Ghoshal, S. Social capital, intellectual capital and the creation of value in firms. AMPROC 1997, 35–39 (1997).
83. de Montjoye, Y.-A., Stopczynski, A., Shmueli, E., Pentland, A. & Lehmann, S. The strength of the strongest ties in collaborative problem solving. Sci. Rep. 4, 5277 (2015).

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