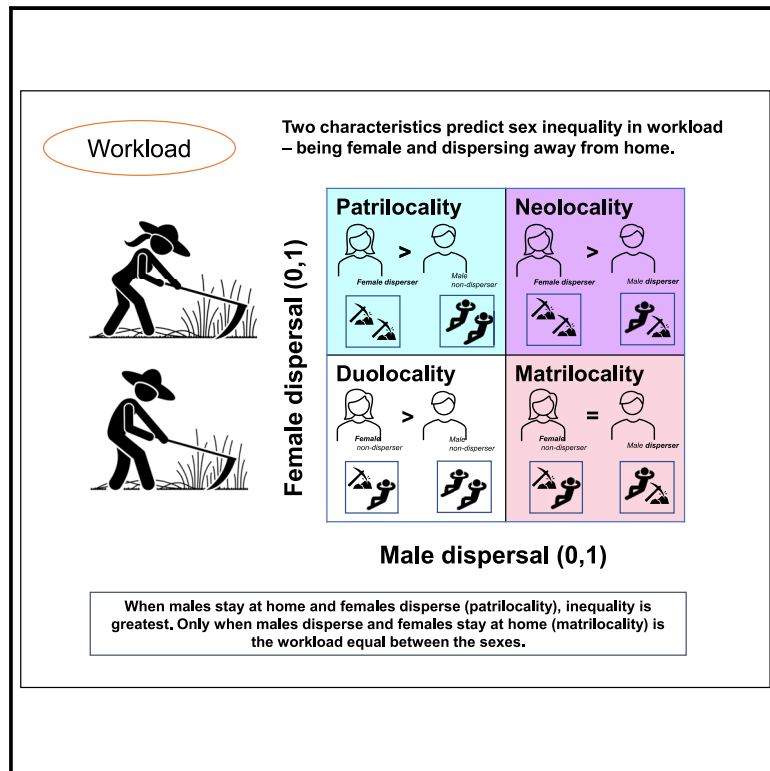# Sex inequality driven by dispersal

Graphical abstract

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In brief

Chen et al. provide cross-cultural evidence that sex-biased dispersal is interacting with social structure to affect an individual's labor contribution in couples among agriculturists and pastoralists. These findings suggest that being female, and dispersing at marriage, are both unfavorable characteristics in the division of labor.

Highlights

- Women work harder and more intensively than men across populations

- Males under duolocality and patrilocality work much less hard than females

- Dispersing at marriage generates a disadvantage in bargaining over workload

- Individuals in larger households work less than those in smaller households

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Sex inequality driven by dispersal

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SUMMARY

Inequality between the sexes is pervasive both outside and inside the home. One contributing factor could be the dispersal of one sex at marriage that sets up sex-specific differences in relatedness to the group. Here we exploit the ecological diversity and different social structures found in southwest China to investigate the role of sex-biased dispersal on inequality in the sexual division of labor. We use a wearable fitness tracker and validated readings by confirming that participants' daily "steps" were positively correlated with time spent in high-energy activities, such as agriculture and animal husbandry work, and negatively correlated with low-energy activities, such as leisure and relaxation. We applied multilevel comparative approaches to examine the relative workload pattern between the sexes under different dispersal states. Our results reveal two characteristics that lead to an unfavorable division of workload: being female and dispersing at marriage. This is consistent with the hypothesis that males have increased bargaining power when remaining in their natal home, leading to inequality in workload.

INTRODUCTION

Deriving from Hamilton's kin selection framework, individuals are more ready to help their kin than strangers, other things being equal.[1,2] Yet kin competition may also exist and limit the evolution of helping behavior intrahousehold, especially given asymmetric relatedness between sexes.[3–11] Dispersal is one such population-level process, which is believed to influence the resolution of family conflict and generate kin-relatedness asymmetry.[6,12] The costs and benefits of dispersal may depend on the cooperation and competition between ego and co-residing kin.[8] Consequently, helping behavior may be sex specific.[13–19] Children may be viewed as shared goods, whereby both parents receive equal genetic benefits, yet one parent often invests more heavily than the other.[20] An evolutionary ecological perspective predicts that males and females may have distinct priorities regarding mating and parental strategies, and bargaining power may determine how much each sex contributes to the household.[20,21] Here we measured the division of labor in a natural context, across a range of populations and cultures, to test the hypothesis that sex and dispersal status are related to the balance of workload between the sexes.

Hunter-gatherers show a clear sexual division of labor between hunting and gathering, often associated with mating strategies,[22,23] although recent archaeological evidence from the Late Pleistocene suggested that females may also have participated in early big-game hunting 9,000 years ago.[24] In agricultural and pastoral societies, the division of tasks between sexes is more variable. Based on visual scans, hunter-gatherers in the Philippines showed roughly equal amounts of leisure time

between men and women, but the balance became more detrimental to women as "off-camp" work increased.[25] Among farmers, males and females share numerous activities, although women often contribute more time and energy to domestic chores, animal husbandry, agriculture, and other family activities, while men's contribution is more limited to agricultural activities.[26–29]

Most work on sex differences in workload has used visual scans and time-budget data.[28] Technological advances now allow more detailed data collection on physical activity and work burden. Using accelerometers, studies on human health tend to focus on modern urban contexts, where activity is beneficial for older people[30–32] and children[33–35] in environments where obesity is a risk. However, in high-workload contexts, a heavy disparity in workload can be harmful to human health,[36] especially for women.[37,38] Women worldwide enjoy less leisure time, involving more unpaid work as previous studies have stated, particularly when multitasking,[39] which can be responsible for fertility decline.[40] Accelerometer data predict human motion and have been validated statistically.[34,41–44] However, most such work has been done in the lab[35,41]; very few studies are in a free-living environment,[45] and even then, most focus on specific tasks.[46,47] There is not much research in agricultural and animal husbandry societies using this technology that compares both sexes across all kinds of physical activity in ecological contexts where high physical activity levels are indispensable to survive and reproduce. Despite the centrality of physical work in everyday life and the strikingly gendered nature of work in most populations, theories of how family structure influences the sexual division of labor are not well developed.

Social structure and the sex-specific demography of populations may influence the residential group's relatedness, hence determining the costs and benefits of helping household members of different ages and sex.[3,7,48–50] Dispersal at marriage, which generates different postmarital residences, is therefore likely to have an impact on the cooperative division of labor in the household.[51–54] It is possible that dispersal away from kin reduces cooperation and hence work for the household, or alternatively, the lack of kin support may reduce bargaining power and thus increase workload.

Here we collected accelerometer and time-budget data on workload from 561 people from a range of rural households in southwestern China. Various ethnic groups inhabit the same ecological area, but their kinship systems and residence patterns are diverse. We investigated ethnic groups located in Sichuan Province and Gansu Province. Figure 1 shows the locations of the Han, Yi, Mosuo, Zhaba (also known as Zaba), zhAmdo, and mqAmdo populations. In China, Mosuo and Zhaba farmers are the only remaining matrilineal societies that still practice "visiting marriage" (also called "duolocality" in anthropology),[55] which refers to couples staying with their birth family and living apart from their partner after pair-bonding, which is extremely rare globally. In matrilineal groups, houses and farmland are usually inherited down the female line. The other four ethnic groups are patrilineal, of which the Han and Yi are mostly agriculturalists, while zhAmdo and mqAmdo people are nomadic or agropastoralists. In patrilineal groups, houses and farms are usually inherited down the male line. Marriage bonds are weaker in matrilineal groups[56] because, for a woman living with her natal family on her own family farm, the consequences of divorce are less costly than for a woman who is living on her husband's family farm and is reliant on her husband's property. However, these systems do have diverse residence patterns both within and between groups. Patrilocality (females disperse to live with their husbands' families), matrilocality (males disperse to live with their wives' kin), and neolocality (both sexes disperse at marriage) are residence patterns all followed by some families in the patrilineal groups (see Table 1).

This diversity provides a "natural laboratory" to examine who benefits most from different kinds of dispersal at marriage, with the additional advantage that the data are from multiple villages and locations where the same team collected the data within one country. We explore the ecological diversity and different social structures found in southwestern China to examine whether sex-biased dispersal is a disadvantage to the dispersing sex.

Technological advances arising from wearable fitness tracking enable us to address these questions on a much larger scale than was previously possible. The accelerometer data provide accurate measures of work rate. The time-budget data, while a more subjective measure based on recall, give insights into how the emerging differences in workload arise. This is the first large-scale comparison across different ecologically relevant contexts that examines how workload (overall physical activity) is determined by sex-specific demography and dispersal.

RESULTS

Our analysis revealed that two main factors are associated with an unfavorable division of workload: being female and dispersing away from one's natal home.
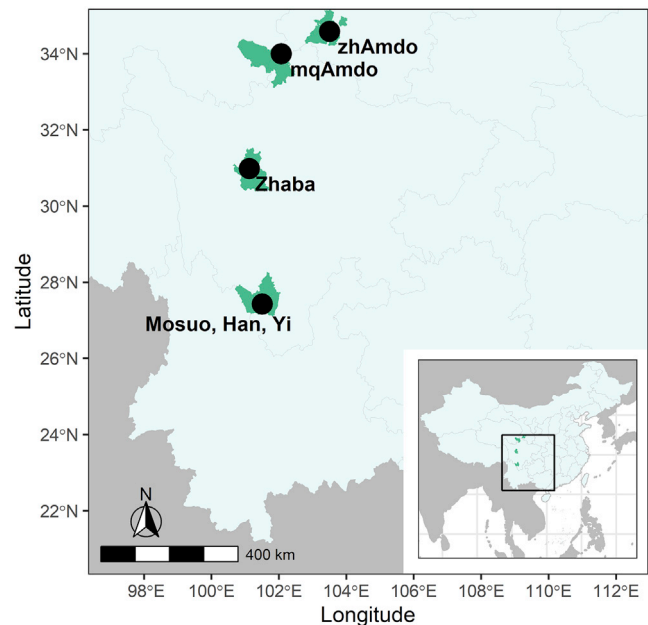

Figure 1. Location map of the study areas in southwest China
ZhAmdo, mqAmdo, Zhaba, Mosuo, Han, and Yi represent six ethnic groups. On the map of China, the four field sites—Zhuoni County (zhAmdo), Maqu County (mqAmdo), Daofu County (Zhaba), and Yanyuan County—are highlighted in green (mixed populations co-reside here). Interviews with Mosuo, Han, and Yi took place in the same ecological setting in Yanyuan County's Lugu Lake area. Southwest China is depicted on the map of China in the inset plot as a squared black box.
See also Table S3.

Differences in overall workload by sex and age

Our results show that females took more steps than males per day across these six ethnic groups (Table S4). There was no sex difference in age distribution or household size, indicating no sample bias (men, n = 267 observations, mean age = 48.74, SD = 13.63; women, n = 294 observations, mean age = 47.29; SD =13.27; also see Table S4). Women walked at an average daily step count of 12,045.78 ± 2,748.53, while men walked 9,026.26 ± 2,997.40—after we applied multilevel model approaches with the ethnic group as a random effect—and the estimates of all multilevel candidate models indicate robust sex difference in the overall daily labor effort, adjusting for body mass index (BMI), any removal of the activity tracker, and being under unusual conditions during pregnancy, lactation, and illness (Table S6).

Our response variable, step counts per day (the proxy of overall daily workload) formed an age-dependent inverted U-pattern between sexes; as individuals grew older, their workload increased to reach a peak around their later mid-life, followed by a gradual decline until end of their lives, presented by raw person-level and day-level data (Figure S2). We generated multiple days of step-count data from the same person based on their full days wearing the accelerometer (days worn) and performed multilevel analysis for the day-level activity data (n = 640 days). As seen in Figure 2, individuals aged over 60 made a labor contribution of 4,578 fewer daily step counts than those aged 30–40 and 3,386 fewer than those aged 40–50. There was no substantial difference between the oldest

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Table 1. Sample distribution of those providing time-budget data by postmarital residence for the six ethnic groups

Ethnic group	Matrilocal	Patrilocal	Duolocal	Neolocal
ZhAmdo	13	35	0	0
Han	1	28	0	22
Mosuo	15	14	51	24
MqAmdo	13	34	0	9
Yi	6	66	0	14
Zhaba	28	16	77	3

We categorized postmarital residence for married people into matrilocal (male disperse), patrilocal (female disperse), duolocal (neither sex disperse, a couple lives apart), and neolocal (both sexes disperse) after marriage (n = 469 people, people-level data). Among these people, 438 currently married people were available for workload analysis, providing 640 full days of accelerometer data. See also Table S4 for day-level sample distribution and Figure S2 for detailed descriptive plots.

group and age group of 50 and 60. Model comparison results are displayed in supplemental information (Table S6). The age differences remain robust to days worn, suggesting consistency in day-level and person-level data (Figure S3). More days worn correlated with a less daily work effort, implying a complementary labor pattern over consecutive days. Nevertheless, this effect is not significant.

Overall, the multivariate multilevel model provided robust evidence of substantial differences between sex and age groups among these ethnic groups and also with various forms of social organization. These differences persist strongly even after controlling for the biological factors of BMI or other unforeseen environmental factors, such as removing the activity tracker during participation in the study.

Differences in workload by social organization
Households with more than eight people had an average step count of 9,547 ± 2,982, while individuals in the smaller households took 11,450 ± 3,304 (p < 0.001, multivariate multilevel modeling; Figure 3A). Household size is significantly negatively correlated with daily step counts among candidate model lists, but the contribution to daily workloads is very small compared with other co-variates in the model (Figure S3; Table S6).

Some groups have duolocal residences, and men under duolocality usually live separately from their spouses and their biological offspring. Duolocal households tend to be large, whereas neolocal couples tend to have the smallest household sizes (Table S4). Our data also show that duolocality is more prevalent among younger couples (Table S4).[8]

By comparing the differences in step counts between the four postmarital residence patterns, we discovered that neolocal couples (both sexes disperse) take the most steps, while duolocal "walking marriage" couples (neither sex disperses and spouses live apart) take the fewest (see Figures 2 and 3B, predicted from the best-fitting model). This implies that men's activities are mostly responsible for the differences. Only in matrilocal households (males disperse at marriage, while females stay) were there no significant sex difference in the number of steps, which is the only postmarital residence pattern in which men disperse to live with their wife's kin (Figure 2).
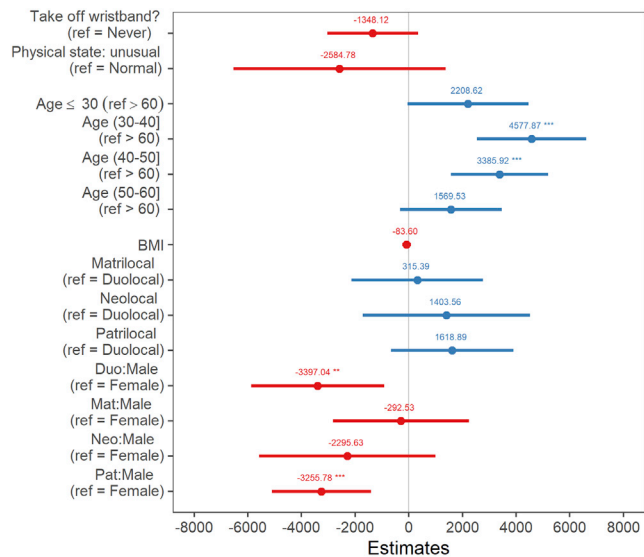

Figure 2. Forest plot of generalized linear mixed model
Estimates show how many step counts vary with postmarital residence pattern (PMR) for 566 married adults' daily observations. Control variables included whether they removed the wristband at any time, were breastfeeding or other unusual situations, body mass index (BMI), and age cohort. "Duo," duolocal residency, neither sex disperses after marriage. "Mat," matrilocal residency, the husband disperses to live with his wife's kin. "Neo," neolocal residency, both sexes disperse after marriage. "Pat," patrilocal residency, the wife disperses to live with the husband's kin. Village ID was set as a random effect. Significance: ***p < 0.001, **p < 0.01, *p < 0.05.
See also Tables S4 and S6 and Figure S3.

As an alternative way to measure postmarital residence, we also explore individual dispersal status. We find that individual dispersal status, age group, and sex remain important (Table S6). BMI, the removal of activity trackers, lactation or being unwell, and household size are all insignificantly negatively correlated with daily step counts (Table S6). We tested models with and without a sex-dispersal interaction: when both main effects of sex and dispersal are present, the interaction is not significant (b = 651.11, 95% CI [−1,988.30, 3,290.51]; see also Table S6), implying that dispersal is a disadvantage independent of sex that is driving individual workload variation. The dispersal model and the postmarital residence model had no significant differences (LR = 2.02, p = 0.73, ANOVA). Furthermore, separating the married sample by sexes revealed significant differences between dispersing and nondispersing men (b = 1,865, SE = 941, 95% CI [47, 3,684]), but not between women (b = 1,199, 95% CI [−763, 3.16]). This suggests a greater disadvantage of dispersal for men. Figure 4 shows a direct view of the interaction between personal dispersal status and sex, where the model revealed that being female and dispersing are the two key characteristics contributing to greater workload (as indicated by daily step counts) (Figure 4).

The increase in the workload of dispersing individuals, compared with those living in their natal households was about 2,000 steps per day (b = 2,069.67, 95% CI [798.54, 3,533.84], multilevel modeling). Controlling for days worn, dispersing individuals also took significantly more steps than nondispersing individuals (b = 1,947.11, 95% CI [647.16, 3,247.06], multivariate
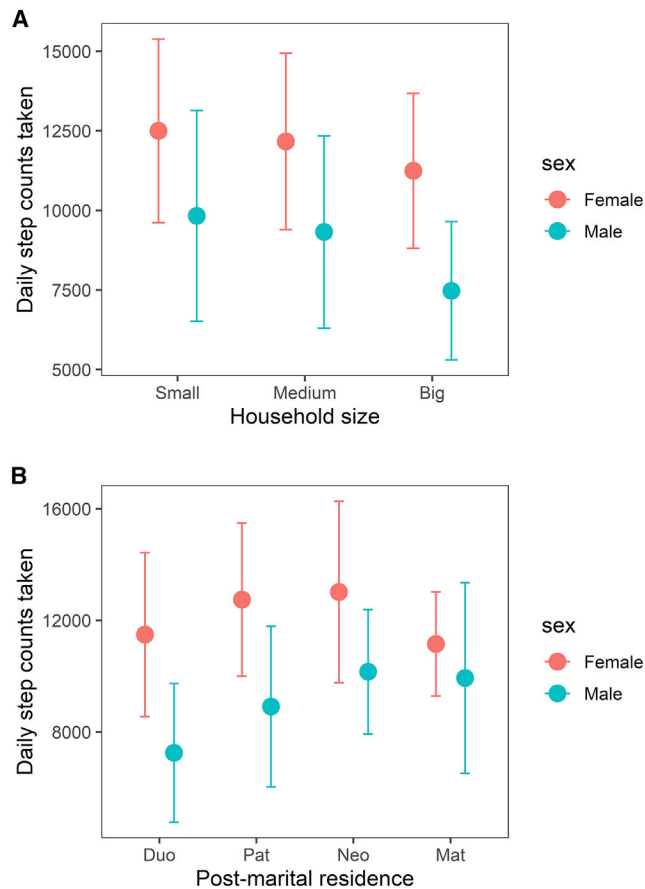
Figure 3. Adjusted workload pattern predicted from generalized linear mixed model (GLMM) varies by postmarital residence pattern and household size across a different social organization (N = 566 days of observation)

(A) Steps and household size pattern.

(B) The effect of sex and place of residence on workload (steps). "Small" indicates a household with fewer than 4 residents; "Medium" indicates 4–8 residents, where 4 and 8 residents are included; "Big" indicates more than eight residents in the household. Duo indicates duolocal residency (both sexes stay at their natal birthplace and practice the walking marriage); Mat denotes matrilocality (males disperse to live with their wives' kin); Neo refers to neolocal residency (both sexes disperse at marriage); Pat means patrilocality (females disperse and live with their husbands' families after marriage).

See also Tables S4–S7.

Figure 4. Interaction effect between sex and individual dispersal status (N = 640 days)
See Table S6.

multilevel modeling). The best-fitting model predicted that dispersing group walked 11,749 ± 3,165 steps per day (n = 354 days of observations), while nondispersing group walked at an average of 9,935 ± 3,040 steps daily (n = 286 days of observations); additionally, dispersing males worked more compared with nondispersing males (dispersing men, n = 113, mean = 10,030; nondisnpersing men, n = 165, mean = 8,370.34; b = 1,801.94, 90% CI [232.20, 3,371.67], multilevel modeling). Overall, these results reveal the role of dispersal in driving sex inequality and possibly explain why globally males rarely disperse.

Differences in activity budgets by sex

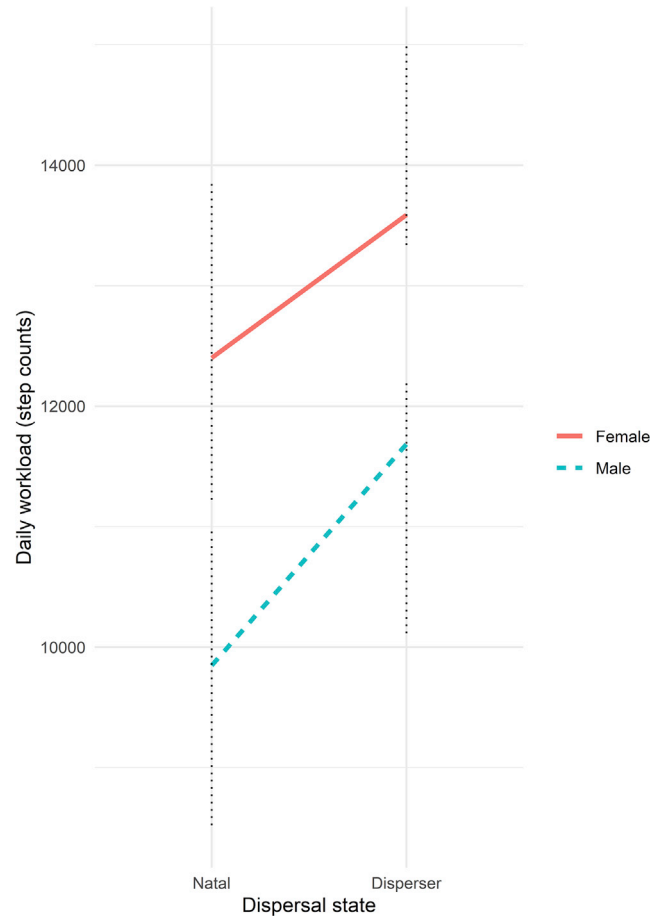In addition to the data from the accelerometer, we collected time budgets by recall over the last 24 h. While this is a more subjective form of data, it enables us to see how it is that some of the differences in activity that we have described may emerge.

Females are more active and spend more time than males in all work intensities of agricultural and animal husbandry, according to self-reported time budgets (Figure 5). Females spent significantly more time than males doing moderate-intensity domestic chores like cooking, laundry, and sweeping (mean, male = 18.247; mean, female = 88.402), as well as some moderate-intensity agricultural and animal husbandry work like cow feeding and milking (mean, male = 59.584; mean, female = 91.243). Women also appear to spend more time on "gathering" activities (Figure 5) (mean, male = 11.673; mean, female = 20.612); this is largely mushroom collecting on the peaks of high mountains, which is a traditional, energy-intensive manner of supporting a family that mainly occurs in Zhaba areas.[57] Men (mean age = 45.87, N = 267) in our sample are more engaged in building and entertainment than women (mean age = 44.96, N = 294), and they reported spending a lot of time playing with their cellphones and watching television. Men with duolocal postmarital residence are involved in lots of political activity and social engagement.[49] When controlling for any broad cultural difference among these populations, the sex difference in time spent working remains robust (Figure S4).
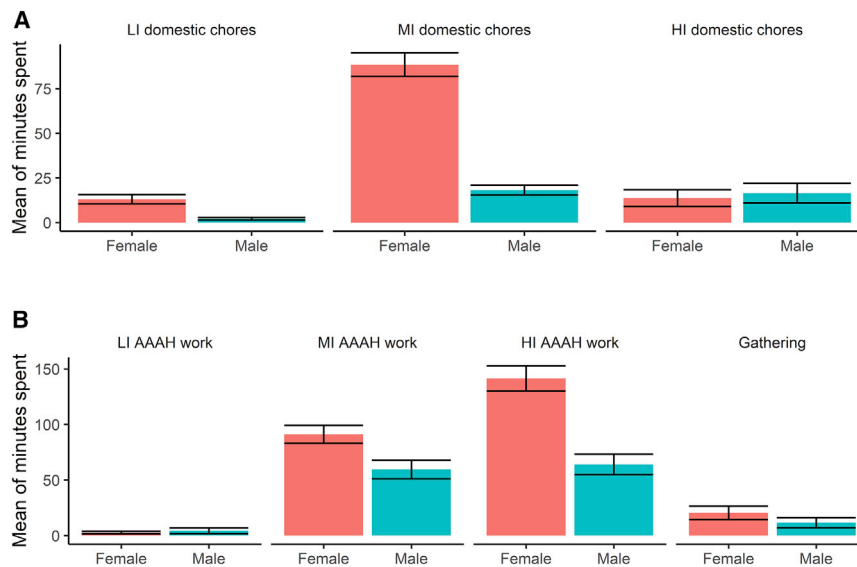
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Figure 5. Time spent on work of different intensity by sex
Mean minutes spent in (A) household chores and (B) subsistence work by sex (N = 561).
LI, low-intensity work; MI, moderate-intensity work; HI, high-intensity work. "AAAH" work represents agriculture and animal husbandry work and gathering, e.g., adopting mushrooms at the top of high mountains. Blue indicates males and red indicates females. Standard errors are displayed.
See also Figures S4 and S5 and Table S7.

By setting up multilevel models, our data confirmed the previous linear regression results that women are significantly more dedicated to both intra- and out-of-household work (Figures 5 and S4). Three separate categories of work referring to wage labor indicate no sex difference (Figure S4, activity codes for wage labor work: AT8–AT10). Combining the result of substantial sex differences in household production and marginal effects of sex on wage labor supported our detailed 24-activity-category design. Significant sex differences are seen in house construction, even though the interpretation of this should be careful, as residents also construct houses for other families, as a traditional form of labor exchange. Therefore, house building may serve as a status or social signal. We also show that men spent more minutes on self-care (AT17), amusement (AT20), driving (AT21 and AT22), and other activities (AT24) (Figure S4) than did women.

Sex difference in energy consumption among light-intensity, moderate-intensity, and high-intensity work
Using the intensities of physical activities, we established a crude classification for these 23 categories (the 24th is other activities; see activity codes in Table S7) into three groups: light-intensity physical activity (LMET), moderate-intensity physical activity (MMET), or high-intensity physical activity (HMET), after Ainsworth et al.[58] The metabolic equivalent task (MET) levels are a general indicator of metabolic consumption and physical activity energy use,[58] referring to the ratio of the energy expenditure rate for activity compared with resting energy expenditure. The comparative outcomes of ego's percentage of time spent in LMET, MMET, and high-intensity activities show that men devote more time to LMET activities (Figure S5), while women devote more time to HMET activities (Figure S5); there was only a minor sex difference in time spent in moderate activities (Figure S5).

The relative difference in time allocation of diverse activities defined by their physical activity level among ethnic groups and sex agreed with results from the accelerometers. Ethnic groups were included as co-variates, and villages were treated as random effects, which is consistent with previous model construction in predicting daily steps taken. Men's time spent in activities of high intensity is highest in the Han group (who are mainly neolocal), while women's highest time contribution of high-intensity (HI) work is found in Zhaba (who are mainly duolocal) (Figure S5). Amdo women (who mainly live in patrilocality) are less likely to be involved in work of light intensity than are men. Further, our data suggested that the dispersers appear to be more engaged in vigorous-intensity activities than those who stay with their natal family, although the effect does not reach statistical significance.

Men aged 30–40 appear to spend higher percentages of their time on vigorous-intensity work than other age groups, and they do less light-intensity activity (Figure S5). Women aged 40–50 have a greater participation rate in high-intensity work compared with the oldest group aging over 60 (Figure S5). Our data show women's workload is more age dependent, while men's time allocation is more dependent on the intensity scale of physical activities.

This further analysis of the pattern of energy consumption revealed consistent sex differences in time budgets across the different populations that support the conclusions of sex differences in overall activity found in the accelerometer study.

DISCUSSION

Our study demonstrates that sex differences in work burden are substantial in these farming and herding communities. Workloads in this region are high. Women, in particular, woke up extremely early in the populations we studied, notably for milking; they also had to feed livestock, prepare food, and gather cow or yak dung for heating and cooking. Independent of the postmarital residence (dispersal) pattern, females do more household and more subsistence activities (farming, husbandry work, gathering work) than males, whereas males are engaged in more building work and leisure. This generally results in a workload penalty for women. Men may have more bargaining power simply by being the physically stronger sex. Sex differences in parental investment are strongly influenced by the mating system.[21] While not all the work done here is necessarily a parental investment, farming and domestic chores are a large part of the workload, and both these tasks contribute directly to children's growth and well-being.[59] Sexual conflict means that men can often benefit from investing in themselves, referring

to private gains,[23] or seek mating opportunities elsewhere, leading to less family investment[49]; this may be contributing to them doing less work overall.

The magnitude of this gendered imbalance is further determined by the social structure of the household. We find that those who disperse at marriage, be they male or female, suffer an additional penalty, doing more work than those who stay in their natal home. Men may choose not to disperse so as to reap the benefits of proximity to their kin and their social networks in their natal areas. There is an equal gender balance in work only if married males have dispersed to live with their wives' natal families. Relatedness to individuals in the household may influence negotiating power.[60] The cost of dispersal could be high at first; however, dispersers benefit from increasing relatedness to the household as they age because they produce more offspring in their new household.[9,61,62] Male dispersal may be rare globally because married men do more work under matrilocal (i.e., uxorilocal) postmarital residence; this fits with accounts from Malawi of men living in matrilineal households being expected to work hard on their wives' farms.[63,64]

Men do least under the patrilocal and duolocal postmarital residence, where the men are living in their natal homes. Men appear to be drawing on the benefits of high relatedness to their natal household to reduce their workloads in these households as predicted. However, females in duolocal households, who are surrounded by their matriline and highly related to all the other household members, work harder relative to their brothers. Duolocal residence is hard to compare directly with the other groups as this is the only case where husband and wife live apart (in walking marriage), sisters are reproducing communally, and men live with their sisters' children rather than their own children.[65] Because the children of the men reside elsewhere (due to walking marriage), this leads to asymmetries in male and female relatedness to the household[7] generating sex-specific differences in competition between siblings. Mothers may invest more in sons compared with daughters due to reproductive competition between their co-resident daughters, but not their sons whose children are in other households, as we have discussed elsewhere.[49,66,67] Theory and data suggest other duolocal social systems in the animal kingdom, such as resident killer whales, are also characterized by mothers preferentially helping their male rather than their female offspring.[68,69]

Middle-aged people's high workloads may reflect their increased relatedness to the household as they get older,[7] in line with predictions on kinship dynamics.[9] The other explanation is that middle-aged people may be indirectly investing in grandchildren, alleviating the workload of their reproductive daughters or daughters-in-law who are breastfeeding and caring for young children.

Additional explanations for sex-specific dispersal include that it may have been driven by warfare and intrafamily conflict.[17] Micheletti et al. found that the sex that competes more locally is more likely to be altruistic, whereas the sex that competes more globally is favored to receive altruism from both sexes.[15] In the case of patrilocality, "boys' clubs," where both males and females preferentially help males, can be generated.[15] Females compete for reproductive resources locally in matrilineal groups, potentially explaining why we observed a high prevalence of cooperative females under duolocal residency.

The sex difference in our farming and herding sample contrasts with results in hunter-gatherer populations that have shown that males walk over 18,000 steps per day on average, more than females who take 10,921 steps on average[70]; and males spent more time in forest work among agro-pastoralist in Nepal.[28] Our results also differ from findings among Hadza foragers in Tanzania, where fat-free mass was the strongest predictor of total energy expenditure (TEE), but in studies that took fat-free mass into account, there was no relationship between TEE and sex, physical activity, or workload.[60] In a recent study on physical functioning in Hadza foragers and Pokot pastoralists in East Africa, sex was not correlated with time spent in moderate to vigorous physical activity (MVPA).[71] In an industrialized setting, the United States, males took more steps than women (5,340 versus 4,912 steps per day).[72] A cross-sectional study focusing on 46 countries studied the association between obesity and activity inequity using smartphone data, and it was found that the Chinese walked over 6,000 steps on average daily, while in South Africa, Indonesia, and the Philippines, people walked fewer than 4,500 steps, and American adults walked 4,774 steps on average.[73] They discovered obesity was negatively correlated with activity per day in this sample of mainly high-income countries (where physical workloads are lower). Evaluating the relationships between workload and health is challenging, but in this context of high work burdens, it can be hypothesized that time spent on leisure is associated with increased fitness, but time spent on arduous subsistence work is associated with increased health risk. The interpretation of self-reported time-budget data should be cautious. However, the differences between our cross-cultural data from farmers and herders and hunter-gatherer data provide insight into the likely association between subsistence systems and sex differences in workload patterns in human communities.

Group living represents a puzzle when there is reproductive competition between co-residents.[74] Communal living and breeding are often interpreted as resulting from a restraint on breeding opportunities or living space,[75] but our results suggest it may also generate efficiencies. The reduced workloads in large farming households suggest economies of scale, and this increased efficiency may underpin why group households form in societies such as the duolocal Mosuo and Zhaba.

In conclusion, we discovered that being female and dispersing at marriage are two factors that contribute independently to an unfavorable division of labor. This suggests that dispersal away from kin appears not to reduce cooperation; rather the lack of kin support reduces bargaining power. Males in particular appear to have greater bargaining power when they stay in their natal family. Leaving the immediate help of family appears to raise the relative work burden in domestic life. This may explain why males rarely disperse. Female dispersal at marriage is the most typical pattern of dispersal globally,[52] leaving most women shouldering the double burden of their sex and their postmarital dispersal contributing to gender inequality in workload.

Strengths and limitations

The research design minimizes response and sampling bias in a cross-cultural, quasi-natural setting, collected across many villages and locations with diverse social structures within one country. Data are obtained independently from reported time

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budgets and activity trackers, presenting consistent results. The comparative nature of the data warrants the conclusion that being female and being the dispersing sex both mean one works more. Compared with observational scans, the step counts, equivalent to 1,440 min per day, validated by time budget, enable us to fully capture the full activity expenditure of individuals, not only during the day but also at night.

One important limitation of this study is that the association between workload and fitness is hard to resolve. Step counts per minute associated with walking at 3 METs differ between sexes, which may contribute to part of the sex difference in our study. Other studies have found that men took more steps than women to reach an equivalent energy consumption per minute.[46]

Time-budget data also revealed that men spent more time in activities of light intensity, whereas women took more time on activities of moderate and vigorous intensities from a set of multivariate multilevel models. The percentages of time spent on each activity of various intensities appear to be sex-specific and depend on ethnic group. Combining these activities and simplifying categories based on the intensities of time-budget data by splitting them into three categories must be treated with caution, as it is a crude measure.[14] Our workload proxy is a component of both offspring care and a contribution to personal subsistence, restraining our interpretation of the scale of offspring provisioning.

Sex-biased dispersal has been discovered to influence parental care in animals; specifically, the more philopatric sex are found to provide more care under sexual conflict.[14] Here, we present evidence of the contribution of dispersers intrahousehold is higher, probably because more time is spent by dispersers on more vigorous work. Further study could use more detailed and focused variables to disclose the within-pair bargaining power between sexes.

STAR★METHODS

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  - Generalized multilevel comparative analysis

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.cub.2022.12.027.

AUTHOR CONTRIBUTIONS

R.M. conceived the study. Y.C. carried out the analysis and modeling work. Study design and implementation by Y.C. and R.M. Data collection by Y.C., E.G., L.Z., and J.D. Writing by Y.C. and R.M. All authors gave final approval of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Activity data and Demographic data	This paper	UCL Research Data Repository
Codes and outputs of GLMM analyses	https://github.com/YUANDALAO/activity-tracker.git	Sex-inequality-driven-by-dispersal.html
Activity code and classifications	This paper	Table S7
Software and algorithms		
R Project for Statistical Computing	R Project	https://www.r-project.org/
'lmPerm' R package	Wheeler and Torchiano[76]	https://cran.r-project.org/web/packages/lmPerm/lmPerm.pdf
'nlme' R package	Pinheiro[77]	https://cran.r-project.org/web/packages/nlme/nlme.pdf
'MuMIn' R package	Bartón[78]	https://cran.r-project.org/web/packages/MuMIn/MuMIn.pdf
'ggplot2' R package	Wickham et al.[79]	https://cran.r-project.org/web/packages/ggplot2/ggplot2.pdf
'sf' R package	Sumner et al.[80]	https://cran.r-project.org/web/packages/sf/sf.pdf
'stargazer' R package	Hlavac[81]	https://cran.r-project.org/web/packages/stargazer/stargazer.pdf

RESOURCE AVAILABILITY

Lead contact
Further information and requests for resources and reagents should be directed to and will be fulfilled by the Lead Contact, Ruth Mace (r.mace@ucl.ac.uk).

Materials availability
This study did not generate new unique reagents.

Data and code availability

- The de-identified demographic data have been deposited at UCL Research Data Repository, and accession numbers are listed in the key resources table. They are available upon request if access is granted, to request access, contact UCL. In addition, the summary statistics describing these data derived from these data have been deposited at UCL Research Data Repository.
- All original code has been deposited at Github https://github.com/YUANDALAO/activity-tracker.git and is publicly available as of the date of publication.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND SUBJECT DETAILS

Study sites
We conducted a demographic survey over six rural populations in western China, Sichuan Province, and Gansu Province (see supplemental information and Figure 1). All individuals gave their consent, and the People's Govt at each local site permitted this research. This research was approved by Lanzhou University (Dept of life sciences) and the UCL (University College London) Research Ethics committee (no 0449/003).

Study sites were selected to encompass a range of social systems, including groups with both high and low levels of female dispersal at marriage (unpublished data).[6] Patrilocal groups have high levels of female dispersal and are mostly patrilineal (wealth inheritance goes down the male line); whereas duolocal groups have low female and low male dispersal and are matrilineal (wealth inheritance down the female line), and spouses often live apart (Table S3 give basic population details). However, within each ethnic

group, there is also diversity in residence patterns, including in most groups some neolocal households where both sexes disperse. For each household, one adult representative was interviewed about the personal information of all family members, which included name, ethnic group, gender, year of birth, marital status, and dispersal status (see details of Maqu, Zhouni, Lugu Lake and Zhaba study sites and samples in the Table S3). The numbers following each of the residence patterns after marriage both within and between ethnic groups are shown in Table 1.

Overview of the activity tracker (Miband 2)

Studies of wearable activity trackers have not found robust evidence to indicate one model is better than others in terms of accuracy among Lexin, Miband, Fitbit Charge, and other pedometers.[82] We compared Miband2 and Fitbit as alternatives, selected for both practicality and technical support.[82] Some studies suggest that Miband2 is not intensely stable, compared with Fitbit, as Miband2 mainly relies on arm swing.[47] However, activities such as milking which includes moments without walking to produce energy expenditure are also included in our research. Compared to Fitbit, we observed that Miband2 is more stable with the lowest variation coefficient when multiple trackers were subjected to the same activity in a test (see Table S1).

Step counts are raw activity data derived from arm movement, whereas some studies use activity counts (AC) calculated depending on combining the basal metabolic rate and step counts. Previous studies revealed that activity counts might be inappropriate for studying physical activity since they underestimated the daily physical activity energy expenditure (PAEE) when activity counts were converted into kilocalories per kilogram per day.[82] Furthermore, a recent study presented that total energy expenditure (TEE) is independent of body fat, and they found no significant within-individual, among-individual correlation between TEE and body fat.[83] The purpose of this study is to investigate the total raw activity amount individual performed during a day, rather than how many calories they burnt throughout each task. Thus, we use Miband2, and its daily 'step' counts as the proxy of workload for this comparative study in rural areas under different socioecological contexts.

The relationship between step counts and workload

In the laboratory-based experiment, we investigated the relative validity of Miband 2 and Fitbit 2 among four subjects (Table S1). Activity counts were substantially associated with PAEE (physical activity energy expenditure) and EE (energy expenditure), as in prior studies.[82,84,85] Activity counts (AC) values measured from most accelerometers and PAEE have correlation coefficients of over 0.90[77]. However, rather than energy expenditure (calories consumed during work), the goal of this study is to investigate the workload pattern between populations. Although sedentary behaviour has caused public health concerns in metropolitan regions, in our rural field sites, local inhabitants are active or vigorously active for the sake of survival under harsh ecological constraints. Since time allocation during lifespan is a constant consideration from evolutionary perspectives, especially when deciding between mating and household maintenance. However, the time budget raised many concerns about the underestimation of higher PAL. In particular, a slow-moving person may spend more minutes on a single task and hence expend less energy overall than someone with higher METs, highlighting the benefits of accelerometers.

Accelerometers function by integrating an accelerometer signal over a predetermined time interval commonly referred to as an epoch.[82] In the case of our activity tracker, our epoch is a one-minute interval, making it difficult to use the epoch cut points to calculate the amount of time spent at various degrees of intensity, as the choice of epoch length will have a substantial impact on the study results. Because this is a cross-region study involving people from distinct subsistence systems, inhabitants wake up at different hours and begin their workday at different times; consequently, they stop at various times for each activity. As a result, deciding the time cut point is practically difficult. Since the purpose of this study was to examine activity patterns over a few days across populations, the precise length of the epoch is not critically important and hence, the default setting, a 1-min epoch, was used. Furthermore, we sampled these populations during the same busy season and recruited the participants to wear the activity tracker for 2-5 days to avoid environmental restrictions. The overall quantity of workload per day in our study is calculated by adding up the 1-minute interval step count to 24 hours or 1440 minutes in total.

Comparative data collection

We conducted a questionnaire data on-time budgets and activity across a total of 55 villages at six different sites in western China in 2017 and 2018 (see Table S3 for details of the sample). 561 people from different ethnic groups completed the time-budget questionnaire (62 questionnaires were collected from the Zhuoni area, 64 from the Maqu area, 275 around Lugu Lake, and 160 from the Zhaba area), of which 294 were from women and 267 from men (see Table 1). The sample included individuals with four kinds of post-marital residence (see Table 1 for details): patrilocal (female disperse), matrilocal (male disperse) and neolocal (both sexes disperse), and duolocal (neither sex disperses with 'walking marriage', which is only found in Mosuo and Zhaba populations[6–8,49]). Across all these samples, we got data from 536 married people in total (see Table 1).

We obtained 561 people's activity data and time-budget data, after omitting invalid step count data, 536 activity data in the last 24 hrs were left. Among all 561 individuals, 469 were married people with demographic data, and 438 of them provided activity data in the last 24 hrs (Men = 194, women = 244). Six hundred and forty activity observations were provided by 438 married individuals. And we obtained 569 daily observations of 469 married individuals, down to 566 of 394 married people when constructed models with missing data omitted.

Some of those interviewed for demographic information were randomly asked to participate in the activity research. They were asked to wear a plastic removable accelerometer on their left hand (which we refer to as a wristband). Other adult family members

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in the same household at that time who also agreed to wear wristbands were also included in the study. Participants were asked to wear the wristband all day and night until we collected them 2-5 days later. That time span was chosen because a shorter time estimates the daily activity pattern of participants less accurately (for instance, on rainy days, people sometimes work much less); and after 5 days, the recovery rate declines, and the wristbands lose power or can be lost.[32,46,86]

On collection, we conducted a questionnaire on the last 24-hour time budget by recall. This enabled us to validate the electronically collected data on activity by comparing it with the participants' account of their activity over the last day (see also Table S2). We asked if they had removed the wristband at any time. We measured the height and weight of participants in the activity study.

METHOD DETAILS

Validation of activity trackers in the lab

Four participants performed a walking task on the same day, and everyone was asked to wear the two kinds of wristbands at the same time for twenty minutes. We selected 8 Miband2 and 13 Fitbit Charge2 randomly and separated them into two sets (Set 1: Six Fitbit Charge2 + four Miband2; Set 2: Another seven Fitbit Charge2 and another four Miband2). And subject A and subject B were told to wear the same four Miband2 and seven FitbitCharge2 (Set 1) but in a different period, subject C and subject D wore the same four Miband2 and six Fitbit Charge2 (Set 2) but not the same period. And then we calculated the mean steps over the last twenty mins, standard deviation, variance, and coefficient of variance for each round by both bracelets (referred to as Miband2 and Fitbit Charge2) to measure the stability of each kind of activity monitor (Table S1).

Validation of activity trackers in the field

For data validation of wristbands in the field, we randomly recruited three persons in one family to track their daily lives for 24 hours. When we began to follow them, the old male had not woken up, however, the two females (mother-in-law and daughter-in-law) had already started their work. (also see Figure S1.)

The younger female's sleep time we recorded was at 10:10 pm and got up at 5:31 am, which was consistent with what the wristband sleep data showed. In general, females woke up earlier than males. Notably, this younger woman felt a bit unwell and rested at some point in the day. Hence, the workload on that day was lower than usual.

Model validation of step counts

Most previous studies of workload obtained activity information through self-report.[26,27,59,87] Although data obtained from questionnaires is effective, participants frequently ignore some light activity when self-reporting, and participants' physical, cognitive, and emotional conditions can all influence reporting. We used 24-hour recall to estimate time budgets to record time spent on each activity (see Table S7, supplemental information). Combined with the time-budget questionnaire, we used wearable activity trackers to provide more detailed information, including activity frequency, activity duration time, and 'steps' or amount of activity.

Studies of metabolic energy consumption have found that the costs of daily activities vary greatly. We recorded 24 categories of activity in total (see supplemental information: Activity code – Table S7) depending on different metabolic equivalent tasks levels (METs), which refers to the ratio of the energy expenditure rate for activity compared to resting energy expenditure, and we classified some subsistence-related activities into L.I. (Low Intensity, energy expenditure below 3 METs), M.I. (Moderate Intensity, energy expenditure between 3 METs and 6 METs), and H.I. (High intensity, energy expenditure above 6 METs) in our analysis abstracted from the Compendium of Physical Activities.[58]

Our activity tracker (Miband2,[88]) is programmed to record and save activity counts in 1-min intervals. In three ways, we validated our wristbands with workload data. To begin, although these activity trackers had been empirically tested before being released to the public, we placed all the activity trackers in the same sack and recorded every single step count after a given same journey, to examine carefully if they performed consistently, and then we eliminated the two outlier wristbands that were significantly different from the mean step counts. Secondly, we double-checked that the wristbands were recording data corresponding to our time-budget activity data. An example of the raw data from three individuals is also shown in the supplemental information (Figure S1). Lastly, we regressed total step counts as the dependent variable and the previous days' time allocation data as the predictive variable, using a multivariate permutation regression (Permutation tests, also called randomization or re-randomization tests).[89] A few activities, such as teaching and studying (AT8, AT10, AT18, AT19), had a low participation rate; hence six activities were not included in this permutation test (see Table S2). Because step counts are related to height and weight, we made sure to account for that in subsequent analysis. Covariates, like weight and height, did have an impact on the step counts, whereas the results of the generalized linear regression model also revealed that the time reported by participants undertaking subsistence work and gathering (AT3, AT4, AT5, AT7, codes presented in Table S2) was significantly positively correlated with the total counts of steps. When individuals spent more time on self-care and leisure, they took fewer steps. Overall, these results are consistent with what we expect if the step count is an indicator of the individual's workload.

QUANTIFICATION AND STATISTICAL ANALYSIS

Generalized multilevel comparative analysis

Data analyses were completed by R software, in which the "lmPerm" package was used to build the prediction model and permutation test,[76] a non-linear logged multi-level mixed model was built in "nlme,"[77] the model screening process was completed in

"MuMIn,"[78] and "ggplot2,"[79] "sf,"[80] "stargazer"[81] packages were used for figures and tables. In regard to time-budget data and activity data, all the categories of activities and step counts show an overdispersion when we conducted generalized multilevel Poisson models. Additionally, a series of Poisson models did not perform well, even after we applied Poisson distribution and log link for daily step count data, as well as binomial distribution and logit link for proportional time-budget data. Therefore, all the generalized mixed-effects models were achieved with the 'lme' function in the 'nlme' package.

In the presence of a random effect, the generalized mixed multi-level model is an effective way to deal with nonnormal data with a small sample size.[77,90] Besides, by relaxing LMM's assumption that the dependent variable (and residuals) follows a normal (Gaussian) distribution and extending GLM's scope of inference beyond a single random population, GLMMs combine and extend the properties of LMM and generalised linear model (GLM) techniques.[91]

Step counts display a slightly left-biased normal distribution (See Figure S2) despite the fact that it was analyzed as count data in most cases. Ives (2015) recently argued that transformed count data analyzed using LMMs can often outperform Poisson GLMMs.[92] Thus, we applied a transformation to step count data. We used a square root transformation for the dependent variable in all GLMMs (generalised linear mixed models),[93] and we found a consistent outcome between the model of raw step count and of square root transformation (see supplemental information), thus model estimates of raw step counts as the dependent variable were shown in the Result section for direct model interpretation, and the transformed ones were displayed in the supplemental information. To explore whether there is a difference in labor (step counts) between individual men and women under the different post-marital residence patterns, we developed generalized linear mixed models for married people across the six ethnic groups (N= 566 observations); the village was set as a random effect to control for any broader ecological differences between field locations. All the models controlled for age cohort, whether individuals are under some unusual circumstances, e.g., lactating or ill (Y/N), whether participants ever took off the wristband (Y/N), and body mass index (BMI).[45] In addition, the interaction between sex and post-marital residence (PMR) was added to the full model. Due to the non-linear correlation between household size and steps, a power function was needed for the household size variable after model comparison (Table S5). To discover how the relative sex differences in workload vary with the four types of PMR, sex was included as an interaction function with PMR. We did not find a significant association between days worn and step counts, thereby days worn were not included across other candidate models (see Figure S3).

To establish whether these sex differences hold when controlling for individual-level fixed effects (of age, sex, and whether an individual had taken off the activity tracker in the past day), we used generalized multilevel linear modelling to predict individual step counts throughout populations. The distribution of person-level activity data displayed similar results to day-level observations, albeit a detectable difference was discovered between person-level and day-level data in the association between daily step counts and age groups (see Figure S2).

The relative labor demand per household - and consequently the work burden faced by people from various households - can be determined by household size. Given the child policy restrictions, fertility varies only little between households, and a wide range of household sizes will largely reflect the number of adult co-residents. Instead of using the dependent-ratio variable, we used the household size in the following analyses. This is because the elderly in our study population performs a wide range of both intra- and extra-household chores, calculating a relative labor force demand by simply compiling the ratio of non-workers to laborers is not very meaningful. The data displayed no significant association between household size and sex (Est = -0.1855, 95%CI [-0.557, 0.186], univariate multilevel modelling, day-level). Additionally, no significant linear association between household size and age range was discerned (Est = -0.010, 95%CI [-0.024, 0.005], univariate multilevel modelling, day-level). Our data, however, revealed that more individuals aged over 60 years were sampled among smaller households with (Figure S2, day-level), compared to other age groups. This suggests that there may be multicollinearity between household size and age groups when constructing models. Therefore, we compare model sets with and without household size, respectively (Table S6). Comparing models with different functional specifications for household size revealed that a quadratic model fits better than a linear model (Δ AIC = 1, w = 62.2% of model sets, w: weights), but a quadratic model does not fit better than the cubic model in the multivariate models (Table S5). Therefore, the cubic function of household size is preserved in the best-fitting model.