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Exploring individual, social and environmental factors related to physical activity: a network analysis

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ABSTRACT

Objectives Insufficient physical activity (PA) has long been a global health issue, and a number of studies have explored correlates of PA to identify the mechanisms underlying inactive lifestyles. In the literature, dozens of correlates have been identified at different (eg, individual, environmental) levels, but there is little or no direct evidence for the mutual associations of these correlates. This study analysed 44 variables identified as theoretically and empirically relevant for PA to clarify the factors directly and indirectly associated with PA.

Methods A cross-sectional survey dataset of 19 005 Japanese-speaking adults (mean age=53.50 years, SD=17.40; 9706 women) was analysed. The data encompassed demographic and anthropometric variables; self-reported PA levels; perceived social support and environments (eg, awareness of urban facilities for PA); psychological traits and health-behaviour characteristics (eg, personality, motivation, self-efficacy, decisional balance, process of change strategies); and technology use (eg, mobile health apps).

Results Network analyses were performed to select meaningful associations (partial correlations) among variables, which identified nine variables directly positively associated with PA: job/employment status, self-efficacy, perceived social support, intrinsic motivation, stage of change, counter conditioning, self-reevaluation, environment and technology use. Indirect associations (two-step neighbourhood) were identified for 40 (out of 44) variables, implying that most of the known PA-correlates are associated with PA—at least indirectly.

Conclusion These identified associations echo the importance of the multilevel perspective in understanding how people maintain (in)active lifestyles. Interventions for PA could have mixed-level targets, including intraindividual characteristics, social support and physical and digital environments.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Research has identified numerous factors associated with physical activity (PA) to ascertain how people maintain PA and acquire healthier, more active lifestyles although it is hardly known how PA and PA-correlates are directly or indirectly associated with each other.

WHAT THIS STUDY ADDS

⇒ We assessed 44 variables (across individual to environmental levels) that are known to be empirically and theoretically associated with PA among 19 005 Japanese-speaking adults.

⇒ A psychological network analysis revealed that most of the known PA-correlates are associated with PA directly or indirectly, which adds the empirical evidence to the models and theories of PA highlighting the roles of psychological, behavioural, social, environmental and digital aspects.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ The results echo the significance of the multilevel approach—that is, understanding (in)active lifestyles from the perspective of individual characteristics (demographic, psychological, behavioural aspects, and so on) as well as social and environmental factors surrounding each individual.

⇒ These findings will guide stakeholders to specify the factors they should target in their projects (eg, PA promotion) and estimate how those targets correlate with other factors that may lead to active lifestyles.

INTRODUCTION

Insufficient physical activity (PA)—an unresolved issue in modern society[1]—is a known risk factor for a variety of non-communicable and chronic diseases such as diabetes and cardiovascular and respiratory diseases.[2 3] There is an urgent need to develop and deliver effective interventions to promote PA, and a number of studies have been conducted to identify promising intervention targets from different perspectives.[4–10] Demographic variables, such as age, gender and health status, are robust predictors of PA levels.[4] Psychological theories have highlighted the significance of motivation,[5] self-efficacy,[6] attitudes[7] and personality[8] in promoting PA. The rise of digital health, accelerated by the COVID-19 pandemic, has had a considerable impact on lifestyles as the use of smartphone apps and wearable activity trackers has been shown to be effective in increasing PA levels.[9] Macroscopic, public health research has identified barriers and facilitators among social, environmental, and political aspects surrounding

individuals (eg, support by family encouraging PA; access to walking trails; health programmes organised by local municipalities).[10]

Published review works have already provided a comprehensive overview of correlates and determinants of active lifestyles.[1 11–13] Dishman *et al*[11] is one of the earliest, which extracted the factors contributing to regular PA from 41 research papers published during the 1970s and until the mid-1980s. They classified the extracted factors into the following three categories: personal (eg, demographic and psychological factors), environmental (eg, social support, peer influences) and activity characteristics (eg, activity intensity). Trost *et al*[12] and Sallis and Owen[13] followed this line of research, reviewing empirical studies published during the 1990s. They expanded the taxonomy by adding a new category, physical environmental factors (eg, adequate lighting, neighbourhood safety), while updating the existing categories (eg, dividing personal characteristics into demographic/biological, psychological and behavioural factors). Bauman *et al*[1] echo the significance of the person-level (both psychological and biological) factors as well as social and physical environments, all of which can be located in a multilevel framework specifying PA-correlates and determinants at different (individual, interpersonal, environment, policy and global) levels. Although these literature reviews clarified the status of evidence and guided research on PA correlates, it remains vague how these factors are related with each other and which factors are directly and uniquely associated with PA. One of the most comprehensive lists of PA-correlates is given by Trost *et al*,[12] which covers more than 70 factors extracted from published empirical studies that investigated the direct associations with PA. Typically, those factors were studied separately in each empirical study—factor-to-factor associations are expected (eg, individuals with agreeable personality may follow active peers encouraging PA, receive social support and then acquire an active lifestyle) but technical challenges, particularly due to the number of identified factors, prevented researchers from drawing a full picture of the complex direct and indirect associations around PA.

In the current study, we analysed 44 variables encompassing demographic, psychosocial and environmental factors that are empirically and theoretically relevant for PA, using the psychological network analysis. This analytic approach enabled us to reveal the patterns of pairwise conditional dependencies present in a multivariate space (ie, associations between the 45 variables: PA and 44 PA-correlates) and to effectively visualise those patterns of statistical associations in the form of network diagram.[14 15] A network diagram represents each variable as nodes, which are connected by edges to represent statistical associations (eg, partial correlations). Our focus was on: (1) which factors would have a unique association with PA level (after controlling for the other factors in the data); (2) what indirect associations would emerge (or which factors would be indirectly associated with PA); and (3) which factors would be the most central in the network (having the greatest association with other variables in the network; ie, centrality indices).

METHODS

Participants

Participants (N=20 611 Japanese speaking adults) were recruited from a sample-pool database; more than a million online panels had been registered to this database. The sample size was determined for practical and pragmatic reasons: (1) we expected that a large sample size would be required to estimate a network of 45 variables (PA and 44 correlates, with 990 possible associations), and therefore, we aimed for the maximum affordable number considering the financial and human resources that we had; and (2) the collected data were analysed for other purposes (not reported here), which specifically focused on a particular group of participants (eg, mHealth app users) and required a sufficiently large size for the subsample. Eligible participants (ie, being aged >18 years, having a good command over Japanese and residency in Japan) received an invitation for two online surveys separated by a month (early 2023). In the first survey, participants completed questionnaires regarding demographics, levels and readiness for PA, psychological characteristics, social support and environmental factors relevant for PA. The second survey encompassed the current health status and medical histories. For each survey, participants received a small compensation for their participation (online shopping voucher). Of the 20 611 participants, 19 039 completed both the surveys. Data of 34 participants were deemed unreliable; that is, those reported: (1) a height of ≤100 cm; (2) a weight of ≤10 kg; and (3) total active time of >24 hours per day. The remaining 19 005 responses were submitted for statistical analyses. All participants provided informed consent. We reported the results in accordance with Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement[16] and the reporting standards for psychological network analyses in cross-sectional data.[17]

Equity, diversity and inclusion statement

Our team consisted of four Japanese men: one junior researcher and three senior researchers. The study population covered a wide range of age groups with balanced gender. However, the online survey was conducted in Japan exclusively and written in Japanese. We assumed that participants had good language command and internet literacy, which may have affected the demographics of participants and thus may limit the generalisability of the results (eg, individuals with lower socioeconomic status or from more marginalised communities may not be included).

Measures

Overall, we based variable selection on systematic literature reviews, such as Trost *et al*,[12] which summarised and categorised PA-relevant factors into demographic

Table 1 Demographic and descriptive data (total n=19 005)

Variable	Abbreviation*	Mean (SD), n (%)
Age	Age	53.50 (17.40)
Gender (women)	Gnd	9706 (51.07%)
BMI	BMI	22.15 (3.71)
Marital status (binary, yes/no)	Mrt	12 106 (63.70%)
Having a child (binary, yes/no)	Chl	11 860 (62.40%)
Education	Edc	
Middle school		462 (2.43%)
High school		5876 (30.92%)
College or vocational school		4302 (22.64%)
University or above		8213 (43.21%)
Other		152 (0.80%)
Job/employment (binary, yes/no)	Emp	11 358 (59.76%)
Household income (JPY)	Inc	
<3 million		4063 (21.38%)
3–5 million		4638 (24.40%)
5–7 million		2917 (15.35%)
7–10 million		2393 (12.59%)
10 million or above		1589 (8.36%)
No answer		3405 (17.92%)
Total PA (in METs-hour/week)	PA	35.06 (56.94)
Stage of change	SoC	
Precontemplation		4090 (21.5%)
Contemplation		4168 (21.9%)
Preparation		3687 (19.4%)
Action		834 (4.39%)
Maintenance		6226 (32.8%)
Health status		
EQ5D-5L		
Quality of life	QoL	0.82 (0.15)
Health status (VAS, 0–100)	Hls	76.32 (17.60)
Present disease (binary, yes/no)	Dss	8605 (45.28%)

*Abbreviations used in the network diagram (figures 1 and 2).
BMI, body mass index; EQ5D-5L, EuroQol 5 Dimensions 5 Level; METs, metabolic equivalents; VAS, visual analogue scale.

and biological; psychological, cognitive and emotional; behavioural attributes and skills; social and cultural; physical environmental; and PA characteristics. Many of the variables listed here were assessed in the current study as well—table 1 presents an overview of the demographic and anthropometric variables, PA levels and readiness and health status (see also online supplemental table S1 for details regarding reported present diseases). Family incomes were binarised whether participant's income was greater than the average family income in Japan (5 million yen). Education levels were also dichotomised to reflect whether participants graduated a university. These dichotomisations were used for interpretability and comparability as other countries may have different income levels and education systems (eg, middle school, secondary school, gymnasium). Dichotomisation leads to loss of information, but we did not expect substantial influences on the conclusions as the associations with PA were not explicitly hypothesised. There were several exceptions and deviations from Trost *et al*.[12] First, for psychological characteristics, we measured variables related to personality, motivation (regulatory focus; hedonic and eudaimonic motives for activities in general), self-control and perceived social support (table 2). We placed social support under the *psychological* characteristic section as this was the only factor concerning social and cultural characteristics assessed in this study.

Other psychological variables were grouped under the *theory-based* category together with behavioural variables (table 2). These variables are typically drawn from the Transtheoretical model and Self-determination theory, encompassing motivation (specifically for exercise), self-efficacy, process of change, and decisional balance, which often tap into both psychological (cognitive) and behavioural aspects. As we wanted to distinguish between general psychological traits (eg, personality, motivation in general) and the constructs specifically developed in the context of PA and exercise, we decided not to merge the general psychological and theory-based characteristics.

Like Trost *et al*,[12] we assessed physical environmental factors (table 3), representing the presence of sidewalks and bike paths as well as safety from crime and traffic. We expected that access to *digital* (not only physical) resources would also be a key factor to explain PA, and thus, the use of mobile health technology (apps and wearable activity trackers supporting PA) and technology acceptance were added to the list (table 3).

Statistical analysis

To find meaningful associations between the assessed variables, we estimated a network using the *qgraph* package (V.1.9.2)[18] for R (V.4.2.2: R Core Team).[19] This analysis estimated a graphical Gaussian model, in which an edge represents a partial correlation coefficient, indicating an association between a given pair of variables (nodes) after controlling for the other variables present in the network. Meaningful edges were selected by the graphical least absolute shrinkage and selection operator[20] (GLASSO). The best-fit network structure was searched using the Extended Bayesian Information Criteria[21] with the hyperparameter γ (a penalty term of the number of edges) set as 0.5.[14] Prior to network estimation, a non-paranormal transformation[22] was applied because the normality

Table 2 Psychological and theory-based variables

Variable	Abbreviation*	Description	M (SD)
1. Psychological			
1.1 Personality (10-Items Personality Inventory)[48]			
Extraversion	Ext	Assertive and gregarious traits (eg, extraverted, enthusiastic)	3.73 (1.33)
Agreeableness	Agr	Cooperative and trustful traits (eg, sympathetic, warm)	5.01 (1.04)
Conscientious	Con	Organised and reliable traits (eg, dependable, self-disciplined)	4.18 (1.21)
Neuroticism	Neu	Emotionally instable traits (eg, anxious, easily upset)	3.97 (1.23)
Openness	Ope	Inquisitive and unconventional traits (eg, open to new experience, complex)	3.80 (1.15)
1.2 Regulatory focus (Regulatory Focus Questionnaire)[49]			
Promotion focus regulation	Prm	The motivation of gaining desirable results (eg, in general, I am focused on achieving positive outcomes in my life)	27.8 (6.65)
Prevention focus regulation	Prv	The motivation of avoiding undesirable results (eg, in general, I am focused on preventing negative events in my life)	27.9 (6.27)
1.3 Hedonic and Eudaimonic Motives for Activity Scale[50]			
Relax motivation	Rel	The tendency to approach low arousal hedonic activities (eg, seeking relaxation)	19.2 (3.95)
Eudaimonic motivation	Eud	The tendency to approach self-enhancing activities (eg, seeking to use the best in yourself)	16.8 (4.17)
Pleasure motivation	Ple	The tendency to approach high arousal hedonic activities (eg, seeking fun)	14.0 (3.12)
1.4 Self-control (Brief Self-Control Measure)[51]	SC	Self-reported abilities to control impulsive behaviours (eg, I am good at resisting temptation)	43.5 (7.81)
1.5 Social support for exercise (Social Support Scale)[52 53]	SS	Friends and family members support exercise behaviours (eg, exercise with me)	1.94 (1.74)
2. Theory-based (transtheoretical model, self-determination theory)			
2.1 Self-efficacy (Self-Efficacy Scale)[29]	Eff	Self-evaluation of capability to implement PA (eg, I am confident exercising even when I was physically exhausted)	10.2 (4.28)
2.2 Decisional balance (Decisional Balance Scale)[54]			
Pros	Prs	The degree of emphasis on positive aspects of exercising (eg, I would feel more confident if I exercised regularly)	3.17 (0.69)
Cons	Cns	The degree of emphasis on negative aspects of exercising (eg, regular exercise would take too much of my time)	2.45 (0.67)
2.3 Process of change (Process-of-Change Questionnaire)[55]			
Self-reevaluation, reinforcement management and self-liberation	SRF	Assessing self-image with and without an inactive lifestyle (self-reevaluation), rewarding PA behaviour and punishing inactive/sedentary behaviour (reinforce management), and the belief that one can change and commit to act on that belief (self-liberation; eg, you feel more confident when you exercised regularly)	20.6 (6.33)
Dramatic relief and environmental reevaluation	DE	Experiencing emotions about being in/active (dramatic relief) and assessing how an in/active lifestyle influences social environments (environmental reevaluation; eg, you think that regular exercise plays a role in reducing healthcare costs)	12.8 (3.77)
Counter conditioning	CC	Learning more active behaviours that can substitute inactivity (eg, you exercise instead of taking a nap after work)	6.73 (2.51)

Continued

Table 2 Continued

Variable	Abbreviation*	Description	M (SD)
Helping relationships	HR	Finding supportive relationships that encourage PA (eg, your friends encouraging you to exercise)	6.02 (2.58)
Consciousness raising	CR	Enhancing awareness about the causes, consequences and cures for being inactive (eg, you read articles to learn more about exercise)	6.88 (2.68)
2.4 Revised Self-determined Motivation Scale for Exercise[56]			
Intrinsic motivation	Intrn	The exercise motivation driven by pleasure in exercise (eg, exercising itself is fun)	12.22 (3.78)
Integrated regulation	Intg	The exercise motivation driven by one's own value of life (eg, doing exercise and being myself are inseparable)	10.82 (3.79)
Identified regulation	Idn	The exercise motivation driven by a personal value of exercise (eg, it is important to me to exercise)	13.62 (3.83)
Introjected regulation	Intrj	The exercise motivation driven by increasing self-worth (eg, I feel guilty if I do not exercise)	10.47 (3.70)
External regulation	Extr	The exercise motivation driven by external rewards and punishment (eg, I exercise because other people say I should)	6.96 (2.73)
Amotivation	Amt	There is no intention or reason to exercise (eg, I do not know why I exercise)	6.73 (2.82)

*Abbreviations used in the network diagram (figure 1).
PA, physical activity.

assumption was violated for certain (eg, binary) variables (see the online supplemental materials for a sensitivity analysis without the transformation, online supplemental figure S1). Each network diagram was depicted using the Fruchterman-Reingold algorithm,[23] which determines edge lengths depending on the absolute values of the edge weights (ie, nodes with a higher partial correlation have a shorter edge length). On the estimated network, we first focused on the variables that had a direct association with PA. Second, we interpreted the indirect (two-step) associations leading to PA. Third, we computed two centrality indices: strength and expected influence, to explore how

Table 3 Environmental and technological characteristics

Variable	Abbreviation*	Description	Mean (SD), n (%)
Environment (International Physical Activity Questionnaire Environmental Module)[57]			
Housing density	Hsd	Housing density in the neighbourhood (eg, What is the main type of housing in your neighbourhood? *Detached single-family residences*)	2.06 (1.37)
Environment	Env	Evaluation that environment surrounding a house is suitable for exercise and walking (eg, there is so much traffic on the streets that it makes it difficult or unpleasant to walk in my neighbourhood)	40.82 (6.28)
Number of vehicles	Veh	The number of vehicles (motorbikes or cars)	1.33 (1.86)
Technology			
Use mHealth supporting PA	mHl	Currently using a smartphone app or wearable activity tracker supporting PA and exercise	4587 (24.14%)
Technology acceptance (Technology Acceptance Model Scale)[58]			
Usefulness of technology	Usf	Perception that technology tools help one's own works (eg, work more quickly)	13.79 (3.48)
Ease of use of technology	Eas	Perception that technology tools are not difficult to use (eg, easy to become skillful)	13.38 (3.42)

*Abbreviations used in the network diagram (figure 1).

and which nodes were most closely associated with other nodes in the network. Strength centrality is given by the sum of absolute edge weights that a node has. Expected influence is the sum of signed weights, which considers the directions—positive and negative—of associations of a node.[24] Both indices therefore quantify the importance of a given node in a network (ie, how many and how strong connections each node has). Edge accuracy (bootstrapped confidence intervals with 2.5 and 97.5% quantiles) and stability of the centrality indices[25] were assessed using the *bootnet* package (V.1.5; see the online supplemental materials for the technical details, online supplemental figures S2 and S3).

RESULTS

Demographics

Demographic information is presented in table 1. The majority of participants were married (64%), had at least one child (62%), held a job (60%) and had obtained higher education (university or above; 43%). The mean body mass index score was 22.15 (SD=3.71) and the total PA level was 35.06 METs-hours/week (SD=56.94). As 9500 participants (50%) met the levels of PA recommended by the national guideline (ie, 23 METs-hours/week for adults aged <65 years; 10 METs-hours/week for older),[26] our sample might be more active than the general population.

Direct associations with PA

The estimated network is illustrated in figure 1A, presenting all 295 edges (30%: 295 out of 990 possible edges) selected by the GLASSO algorithm. The mean absolute edge weight was 0.09. Panel B specifically illustrates the edges directly associated with PA (one-step neighbourhood). Of the 44 PA-correlates submitted to the network analyses, nine showed positive, direct associations: *job/employment*, edge weight=0.049, IQR = (0.036 to 0.062); *stage of change*, edge weight=0.256, IQR = (0.242 to 0.270); *social support*, edge weight=0.073, IQR = (0.059 to 0.087); *self-efficacy*, edge weight=0.062, IQR = (0.048 to 0.077); *self-reevaluation*, edge weight=0.024, IQR = (0 to 0.037); *counter conditioning*, edge weight=0.067, IQR = (0.055 to 0.081); *intrinsic motivation for exercise*, edge weight=0.037, IQR = (0.025 to 0.050); *environment*, edge weight=0.072, IQR = (0.057 to 0.083); and *mHealth technology use*, edge weight=0.092, IQR = (0.078 to 0.104). Two nodes showed negative, direct associations with PA: *helping relationships*, edge weight=−0.049, IQR = (−0.061 to −0.035); and *external regulation for exercise*, edge weight=−0.058, IQR = (−0.070 to −0.043). These results suggest that the variables that are closely associated with PA can be found at different (from intra-individual to environmental) levels: demographics (job/employment status); psychological characteristics and behaviour change strategies (social support, self-efficacy, self-reevaluation, counterconditioning, intrinsic motivation); physical environments; and technology (mHealth) uses. Not surprisingly, most of these variables are contextualised in PA and exercise (eg, intrinsic motivation for PA, but not motivation in general), and none of the general psychological traits (eg, Big-five personality, well-being) was directly associated with PA.

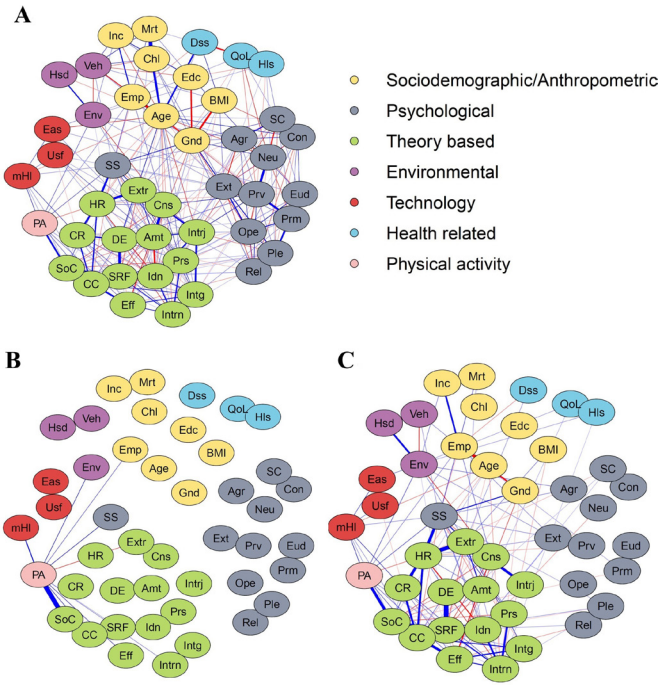

Figure 1 The estimated network of physical activity and its correlates. (A) The estimated network with all edges selected by the GLASSO. The thickness of each edge represents the strength of the association (partial correlation), and the colour represents the direction (blue=positive; red=negative). The node colours indicate the category of factors, corresponding to the headers in tables 1–3. (B) The network with one-step neighbourhood (displaying the edges directly associated with physical activity). (C) The network with two-step neighbourhood (indirect edges added). Abbreviations and descriptions of each node are presented in tables 1–3.

Indirect associations with PA

Panel C in figure 1 represents the indirect associations, namely the edges related to the nodes that are directly associated with PA. This two-step neighbourhood network connected 40 nodes out of the 45 nodes, suggesting that most of the known PA-correlates are associated with PA at least indirectly. Among the nodes directly connected to PA, social support was found to be the most important hub for the other (indirectly associated) nodes, showing the largest number of edges in the two-step neighbourhood network. Social support bridged the associations with PA for demographics (age, gender and marital status); personality and general psychological characteristics (extraversion, agreeableness and pleasure motivation); theory-driven variables for behaviour change (pros and cons; integrated, identified, introjected and external regulation; and amotivation); and physical environments (number of vehicles).

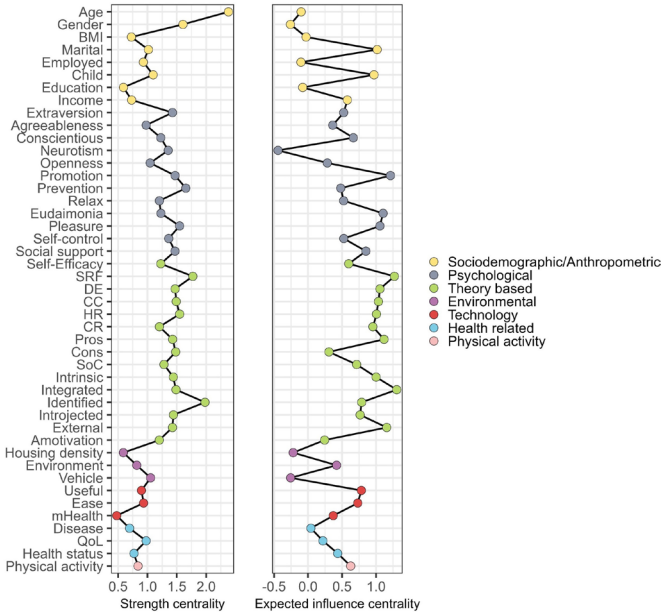

Figure 2 Centrality indices. Abbreviations and descriptions of each variable are presented in tables 1–3. BMI, body mass index.

Centrality

We found the highest strength centrality for age, identified regulation and self-reevaluation (figure 2), implying that these variables had the greatest absolute associations (aggregated) with the other nodes in the network (see the online supplemental materials for individual centrality scores). The highest expected influence (which considers the direction of edges) was identified for integrated regulation, self-reevaluation and promotion focus regulation, showing the largest positive associations with the other nodes in the sum. Neuroticism exhibited the most prominent negative expected influence, which suggests that this personality dimension is typically negatively associated with the variables in the network.

DISCUSSION

Insufficient PA has long been an unresolved health issue, and decades of research has identified numerous factors related to PA at different levels.[1 11 12 27 28] Our aim was to reveal the factors uniquely associated with PA as well as clarify and visualise how the factors are mutually related using the network analysis.

Direct edges

The results identified nine variables, across individual, social and environmental levels, that are directly positively associated with PA: job/employment status, self-efficacy, perceived social support, intrinsic motivation, stage of change, counter conditioning, self-reevaluation, environment and mHealth technology use. As the edges reflect unique associations with PA after controlling for the other variables in the network, these nodes could be interpreted as proximate factors that are closely associated with PA. Four of the variables (self-efficacy, stage of change, counterconditioning and self-reevaluation) are from the transtheoretical model for PA,[29 30] whereas intrinsic motivation and social support (as well as self-efficacy or competence) are highlighted in the social-cognitive theory[31] and self-determination theory.[32] Self-efficacy (defined as confidence in maintaining PA even in the presence of barriers) is known to increase as the stage of change progresses,[33] from the precontemplation (having no intention to start exercise) to maintenance stage (having acquired an exercise habit). Counterconditioning and self-reevaluation are counted as the process-of-change strategies that help people adapt their behaviour to progress through the stages of change. These behavioural strategies focus on internal and external controls (eg, self-image; reward and punishment), which are relevant to improving self-regulation and autonomy as well as self-efficacy. Social support (eg, modelling by family and friends; support from an exercising partner) is another basis of self-efficacy and self-regulation,[34] which are also known to be related to intrinsic motivation.[35] The associations with physical environments and information technology (mHealth) uses are also in line with the literature.[36 37] Our findings suggest that the PA-proximate factors can be found at different levels, but this does not mean that these factors work independently— instead, as the theories assumed, they are mutually associated with each other (see figure 1, Panel A), and there could be a cycle to enhance and maintain PA levels (eg, the use of behaviour change strategies supported by mHealth tools may lead to increased self-efficacy).

On the other hand, direct negative associations were identified for external regulation and helping relationships. The identified negative associations were intuitively difficult to interpret as both external regulation (eg, *people around me (family, friends, doctors, etc) say I should take up exercise*) and helping relationships (eg, *your friends encourage you to exercise*) conceptually overlap with perceived social support (eg, *do you have a significant other, such as a family member, spouse, friend or colleague, who gives you advice or guidance on how to exercise?*). External regulation and helping relationships almost exclusively relate to exercise recommendations from others, whereas social support is operationalised as various strategy supports that one receives, such as how-to tips, coexercising and appraisals. Consistent with our findings, a systematic review concluded that social pressure, like external regulation, tends to have little or even adverse effect on PA.[35] This may suggest that the type and quality of support is significant to determine the direction of the association with PA.

Indirect edges

Another key finding is that the two-step neighbourhood network connected almost all the variables submitted to the network analyses (40 out of 45 nodes). Here, we included as many variables as possible, following the lists of empirically and theoretically relevant correlates of PA

(eg, Trost *et al*).[12] This implies that most of the known PA-correlates are at least indirectly (if not directly) associated with PA, which reassures us that each characteristic from individual to environmental levels (eg, demographics,[4] motivation,[5] self-efficacy,[6] attitudes,[7] and personality,[8] environment[38] and technology acceptance[39]) is significant to draw a profile of someone with an (in)active lifestyle in the context of the multilevel framework.[1] It is also noteworthy that social support worked as the most important hub for PA, connecting the largest number of nodes (including marital status, extraversion personality) in the two-step neighbourhood network. Inter-person factors, particularly social incentives (collaborations and competitions), are known to be effective in improving PA[40] although large heterogeneity has been documented.[41] Causal inference is not possible with our data, but our results may suggest that family status and pro-social psychological characteristics (eg, extraversion) are prerequisites for social support to function effectively. We see the current network analysis as a hypothesis-generation process, and the identified in-direct associations will serve as new hypotheses to be tested in future research using a more hypothesis-driven approach (eg, structural equation modelling) with an experimental or longitudinal study design for establishing temporal and causal relationships.

Centrality indices

Furthermore, the centrality analyses showed the highest strength for age, which was most closely associated with other variables in the network (followed by identified regulation and self-reevaluation). Previous studies have already identified similar associations between age and PA-correlates: for example, personality,[42] exercise motivation,[43] barriers[44 45] and mobile device use.[46] Conversely, environmental barriers have been documented commonly across different age groups.[45] Interestingly, age did not have a direct edge to PA in the estimated network—individual and social characteristics may differ across age groups, but age per se works as a pure indirect predictor, not directly informing PA levels after controlling for other PA-correlates. The highest expected influence was found for integrated regulation, followed by self-reevaluation and promotion focus regulation, which had mostly positive associations with other nodes in the network. On the other hand, neuroticism showed the greatest negative expected influence. These findings imply that motivation and process of change may play—as the transtheoretical model and self-determination theory assumed—key roles in active lifestyles, whereas neuroticism and mental health issues could be a barrier in maintaining individual and environmental factors supporting PA—indeed, neuroticism is related to exercise barriers.[47]

Limitations

Several significant limitations should be noted when interpreting our results. First, the cross-sectional nature of the study limits the ability for causal inference. Bauman *et al*[1] emphasised the significance of identifying determinants, beyond correlates, to develop and establish an intervention that helps efficiently increase engagements in PA. Although we believe that our findings refined the list of PA-related factors by identifying the direct (and indirect) associations, a longitudinal study is warranted to explore potential prospective (and causal) associations among the correlates. Second, we aimed to analyse PA-related variables as comprehensively as possible, but exhaustive assessments with *any* relevant measures were not possible for pragmatic reasons. Critically, the network structure may vary depending on the variables submitted to the analysis, which calls for careful replication with different selections of variables. Third, we solely relied on self-report measures, which may be affected by reporting bias. It would be significant to apply objective assessment methods (eg, accelerometers) in future replications.

CONCLUSION

Notwithstanding these limitations, we believe that our findings make meaningful contributions to the literature—(1) we identified 11 factors directly associated with PA among the 44 factors identified relevant in previous studies; and (2) we visualised the complex direct–indirect associations between the PA correlates. Most of the PA-correlates—from individual to environmental—were indirectly associated with PA, which confirms the significance of the multilevel perspective in understanding the contexts that facilitate active lifestyles. Another unique contribution is that our sample included only Japanese-speaking adults. This may limit the generalisability of our findings to Western populations but may support the validity of the theories and empirical findings (eg, the transtheoretical model) in the East. It would be an interesting direction for future research to identify a unity theory for PA-correlates and determinants as well as explore culture-specific or region-specific factors contributing to PA. Also, we hope that our findings will guide stakeholders (not only researchers but also practitioners and policymakers) to specify the factors they should target in their projects (eg, PA promotion) and to simulate how manipulating those factors will impact PA and lifestyles.

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