Running head: TPB and BPN for sport participation

Understanding sport continuation: An integration of the Theories of Planned Behaviour and Basic Psychological Needs

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Abstract

Objective: Fostering individuals' long-term participation in activities that promote positive development such as organised sport is an important agenda for research and practice. We integrated the Theories of Planned Behaviour (TPB) and Basic Psychological Needs (BPN) to identify factors associated with young adults' continuation in organised sport over a 12-month period. **Design:** Prospective study, including an online psycho-social assessment at Time 1 and an assessment of continuation in sport approximately 12 months later. **Method**: Participants (*N* = 292) aged between 17 and 21 years (*M* = 18.03; *SD* = 1.29) completed an online survey assessing TPB and BPN constructs. Bayesian structural equation modelling (BSEM) was employed to test the hypothesised theoretical sequence, using informative priors for structural relations based on empirical and theoretical expectations. **Results**: The analyses revealed support for the robustness of the hypothesised theoretical model in terms of the pattern of relations as well as the direction and strength of associations among the constructs derived from quantitative summaries of existing research and theoretical expectations. The satisfaction of BPN was associated with more positive attitudes, higher levels of perceived behavioural control, and more favourable subjective norms; positive attitudes and perceived behavioural control were associated with higher behavioural intentions; and both intentions and perceived behavioural control predicted sport continuation. **Conclusion**: This study demonstrated the utility of BSEM for testing the robustness of an integrated theoretical model, which is informed by empirical evidence from meta-analyses and theoretical expectations, for understanding sport continuation.

Keywords: Bayesian structural equation modelling; methodological-substantive synergy; self-determination theory; sport continuation; sport dropout; theoretical integration

Introduction

Participation in organised sport provides a wide range of improvements in key indicators of physical and psychological health. In addition to the vast physical benefits (e.g., cardiovascular fitness, weight control, adult physical activity, decreased risk of diseases such as diabetes and osteoporosis), a growing body of research[1,2] indicates that organised sport has the potential to promote positive psycho-social outcomes (e.g., increased self-esteem, happiness, life satisfaction, positive peer relationships, leadership skills) and foster personal development. Despite these potential benefits, many people do not participate in organised sport. According to national statistics[3], only 26% of Australians report engaging in organised (i.e., by clubs, sporting or non-sporting associations) sport and physical recreation. Of these people participating in organised sport and physical recreation, the highest participation rates (58%) were observed for individuals aged 15-17 years. However, participation rates steadily decrease as people age with the most notable decline occurring in early adulthood, between the ages of 18 and 24 (35% participation). Thus, an important question for future research is, what factors are associated with an individual's continued participation in organised sport?

Social cognitive theories, which encompass both social and psychological determinants of behaviour, are among the most widely adopted frameworks in health behaviour and health education research[4]. The Theory of Planned Behaviour (TPB)[5] is one of the most widely tested social cognitive models because it has been found useful for predicting many different kinds of volitional behaviours (e.g., diet, exercise)[6,7,8]. Within the context of TPB, *intention* to engage in or perform the act under consideration is the most immediate and powerful determinant of that behaviour. Intention, in turn, is determined by three components: *subjective norms* (the perceived social pressure to perform the behaviour), *attitudes* toward the behaviour (the degree of positive or negative evaluation of the behaviour), and *perceived behavioural control* (the perceived ability to carry out the behaviour). Thus, an intention to engage in or perform the act under consideration will be stronger when the attitudes toward the behaviour are positive, when important others support the behaviour, and when the individual believes that s/he has control over engaging in the behaviour. Correspondingly, the stronger the intention to engage in or perform the behaviour *and* one's perceived ability to perform a given behaviour, the more likely it is that the act under consideration will eventuate. Meta-analyses[6,7] have supported these theoretical expectations, with approximately 40-45% of the variance in intentions accounted for by attitudes, subjective norms, and perceived behavioural; in turn, intentions predict roughly 27% of the variance in behaviour.

Owing to the substantial body of evidence to support the theoretical expectations of the TPB, the first aim of this study was test the robustness of the TPB for understanding young adults' continued participation in organised sport because this group evidences significant decreases in participation rates in organised sport and physical recreation[3]. We employed existing statistical summaries of empirical research on the TPB[6,7] to inform our analyses using Bayesian structural equation modelling (BSEM[9]). Adopting a Bayesian perspective enabled us to empirically test the probability of a theoretical model including expectations regarding the direction and strength of relationships among TPB constructs based on previous research, given our data (see Figure 1).

Our second aim was to examine an integrated social-cognitive framework that has the potential to provide a more comprehensive understanding of sport continuation than any single model alone. Theoretical integration, which combines the strengths of different theories to overcome their individual shortcomings, has gained prominence as a means by which to better understand complex health-related behaviours[11,12]. Specifically, we examined the utility of integrating TPB with self-determination theory (SDT)[13] with a particular focus on basic psychological needs (BPN)[14] to provide an insight into the associations between perceptions of the social environment and one's attitudes, perceived behavioural control, and subjective norms towards organised sport (see Figure 1). *Competence* is the need to feel skilled and capable at the task in question, alongside the opportunity to successfully utilise one's skills and knowledge. *Relatedness* is the need to feel socially valued and understood. *Autonomy* refers to the degree to which people perceive themselves as having choice and control within their environment. Conceptually, these three needs are considered equivalent with regard to their importance for psychosocial functioning[15]. As optimal psychosocial development and functioning depends on the satisfaction of all three needs[14], the overall degree of needs satisfaction is often of primary importance[16,17].

The reasons *why* people participate in sport (needs satisfaction) influence social-cognitive variables that predict energy and effort towards volitional behaviour. When people perceive that their social environment supports needs satisfaction, they feel as though they are the originators of their behaviour, and skilled and capable in their actions (cf. perceived behavioural control, instrumental attitudes); socially valued and connected with others (cf. affective attitudes); and are provided with rationales for decisions and processes thereby fostering an understanding of why the activity is important (i.e., subjective norms)[18]. Thus, we propose that one's contextual perceptions of social agents who contribute to needs satisfaction in sport (rather than life in general) may have a direct influence on one's attitudes, perceived behavioural control, and subjective norms towards organised sport. This conceptualisation differs from previous research in which global-level needs satisfaction in one's life exerted their influence on social-cognitive variables via autonomous motivation[16].

Alongside the theoretical integration of TPB with BPN, we extended previous research in two ways by considering multiple social agents as they represent unique sources of developmental needs[19]. First, with regard to the sport context, coaches and teammates uniquely influence one's perceptions of the social environment[20] and therefore may differ with regard to the degree to which they satisfy BPN. Consistent with theoretical[14] and empirical expectations[18], needs support from both adult leaders (e.g., coaches) and peers should have a positive association with subjective norms, attitudes, and perceived behavioural control. Second, the operationalisation of norms within the TPB as an overall summation of different referents may underestimate influence if non-salient agents are referred to when reporting one's perceptions. As parents and peers are key agents for psychosocial development during adolescence and adulthood[21], individuals may base their future sport involvement intentions on norms from both their family and peers. Guided by related research[22], we expected peer norms to be more important for behavioural intentions than expectations perceived from the family unit.

Methods

A total of 292 individuals completed assessments at two time points (91.25% retention). The sample included both male (n = 75) and female athletes (n = 213) aged between 17 and 21 years (M = 18.03; SD = 1.29); four individuals did not report their gender. Participants were purposefully recruited because they were engaged in organised sport at the first assessment point; main activities reported by participants included a variety of individual (e.g., archery, golf, triathlon, tennis) and team (e.g., Australian football, basketball, rugby league, water polo) sports.

Items designed to target the constructs of TPB were developed specifically for this study, whereas an established 9-item measure was employed to assess perceptions of the satisfaction of BPN[17] (see Table 1). Two points of reference were assessed for subjective norms (family and friends) and BPN (adult leaders and peers) because these individuals are important influences on development and functioning for this age group[19,21]. All items were scored on a 7-point Likert scale. A convenience sample of undergraduate students were invited to participate to receive course credit. We distributed the information sheet to groups of approximately 10 to 20 individuals in a lecture room. Participants were assured of confidentiality and anonymity in responses, and informed of their right to withdraw consent at any time before obtaining their consent to participate. Participants took the information sheet away with them and completed the online survey within 2 weeks of receiving the study information. Approximately 12 months after completing the initial survey, participants electronically reported whether or not they continued with their main sport (yes = 1; no = 0). Institutional ethics approval was obtained prior to the commencement of this study.

We tested the model depicted in Figure 1 using BSEM[9] in Mplus 7.11[23]. All constructs except for sport continuation (dichotomous) were modelled as latent variables including those item indicators detailed in Table 1 and their error terms. We drew from statistical recommendations regarding the quality of factor loadings[24] to guide informative priors for the measurement models. Specifically, we specified intended loadings to have a normal prior of .7 and a standard deviation $\pm$ .28, meaning that these loadings are likely to be between .42 and .98; cross-loadings were designated using zero-mean, small-variance informative priors of .01 thereby representing a 95% credibility limit of $\pm$ .20 (i.e., 1.96 multiplied by $\sqrt{.01}$). Informative priors[25] for the structural relations between the TPB constructs and sport continuation were guided by meta-analytic evidence[7,8] (see Table S2 of Supplementary Material). Theoretical[14,15] and empirical[16] expectations guided our prior knowledge of the relationships between BPN and the TPB constructs. Specifically, informative priors were modelled such that BPN were expected to evidence a positive relationship with attitudes, perceived behavioural control, and subjective norms (see Table S2 of Supplementary Material).

The posterior distribution is generated from the parameter for the prior and observed data using the Markov chain Monte Carlo estimation algorithm, which is founded on the Gibbs sampler method[9,26]. Model fit is assessed using posterior predictive checking, which compares the probability of the observed data against the generated posterior distribution while taking in account variability in the parameters[27]. A posterior predictive p value (PPP) is computed in Mplus to provide an indication of the degree of deviation between the real and replicated data together with a 95% confidence interval for this discrepancy function. Ideally, there should be little discrepancy between the observed and generated data. A small positive PPP value (e.g., 0.05) is indicative of poor fit, and a value around 0.5 and above suggestive of good fit[9]. Model convergence is assumed when the potential scale reduction factor value is $\leq$ 1.1[26] and visual inspection of trace plots indicates multiple chains converged to a similar target distribution[25]. We considered parameters in which the 95% credibility interval (95% CI) did not encompass zero to have gained substantive support[9]. Additional information on the specification procedures can be found in Appendix A of the Supplementary Material.

Results

Descriptive statistics and reliability estimates for all study variables are detailed in Table 2. All measures showed adequate reliability (Cronbach's $\alpha > .85$). The percentage of participants that continued their sport participation did not differ by gender, $\chi^2(1, N = 288) = 0.00$, $p = .99$. The probability of the hypothesised theoretical model depicted in Figure 1, given the data, was excellent (PPP = .685, Δobserved and replicated χ^2 95% CI [-142.62, 87.89]). Two chains were estimated and in 57000 iterations reached an appropriate convergence criterion[26]. Visual inspection of trace plots verified support for convergence (e.g., see Figures S1 and S2 of Supplementary Material), as did an examination of the PSR development over iterations (i.e., smooth decrease in PSR, last few thousand iterations were close to 1)[9]. In terms of the measurement models of each latent factor, all intended factor loadings were good (>.44) and significant, with all cross-loadings small (< $\pm$ .15) and non-significant. An overview of the parameter estimates for the structural components are depicted in Table 2. BPN from peers were found to have low-to-moderate associations with attitudes (95% CI: .14, .35), perceived behavioural control (95% CI: .12, .34), and subjective norms from peers (95% CI: .12, .34) and family (95% CI: .11, .33). There were low-to-moderate associations between BPN from adult leaders and attitudes (95% CI: .14, .35), perceived behavioural control (95% CI: .12, .34), subjective norms from peers (95% CI: .14, .35), and subjective norms from family (95% CI: .03, .27). The association between intentions to remain engaged in organised sport and both attitudes (95% CI: .14, .43) and perceived behavioural control (95% CI: .38, .63) was low-to-moderate and large, respectively; the associations with subjective norms from family (95% CI: -.13, .17) and peers (95% CI: -.09, .22) did not gain substantive support. Approximately 56% of the variance in behavioural intentions was explained by attitudes, perceived behavioural control, and subjective norms. Perceived behavioural control (95% CI: .10, .36) and intentions (95% CI: .35, .63) evidenced a low-to-moderate and large association with sport continuation, respectively, accounting for approximately 46% of its variance. Interested readers can find a comparison of the Bayesian results with those obtained from a frequentist approach in the Supplementary Material.

Discussion

In this study, we applied an emerging methodology – Bayesian structural equation modelling (BSEM[9]) – to examine a substantively important issue; that is, the examination of social-cognitive factors important to an individual's continued participation in organised sport. In terms of conceptual innovation, the theoretical sequence tested in this study integrated the TPB[5] and BPN[14] in an effort to provide a more comprehensive and parsimonious understanding of sport continuation. Specifically, whereas the TPB captures the social-cognitive antecedents of sport continuation, BPN offers an insight into one's affective assessment of external events and the social environment on one's attitudes, perceived behavioural control, and subjective norms towards organised sport.

Recognising that one of the most dramatic declines in sport participation occurs between adolescence and young adulthood[28], the identification of factors associated with university students' intentions to remain engaged in organised sport and behavioural continuation is important considering this transitional period creates a shift in routine and habits that were previously predictable and associated with a sense of control[29]. Consistent with a large body of research[7,8,13], the results of this study underscored the substantive importance of positive attitudes and perceived behavioural control as proximal antecedents of intentions; in turn, intentions and perceived behavioural control both emerged as substantive considerations for understanding sport continuation. In contrast, perceived externally-referenced beliefs from both peers and family did not play a substantive role in understanding intentions to continue playing sport. The weak norm-intention association evidenced here and elsewhere[6] has led some[5] to suggest that attitudes and perceived behavioural control are the primary antecedents of behavioural intentions. The consideration of additional sources of normative beliefs (e.g., descriptive, moral, group)[30] in future research, however, offers potential for delineating a nuanced understanding of the norm-intention relationship.

Consistent with theoretical[14,15] and empirical expectations[16], the results of this study supported the integration of the TPB and BPN for understanding young adults' continuation in organised sport over a 12-month period. Specifically, all associations between BPN from adults and peers with the three determinants of behavioural intention were found to be substantively important. These findings are consistent with experimental evidence in which it has been shown that people enjoy and persist with novel tasks in the laboratory to a greater extent when the conditions support their satisfaction rather than frustrate their psychological needs[31]. Drawing from a hierarchical perspective of motivation[32], these findings provide additional support for a top-down effect of contextual perceptions of the social environment (BPN) to situational factors (TPB)[16]. As these findings are consistent with related research on physical activity[8], these two volitional behaviours may represent partially overlapping phenomena that should be accounted for in future research; for example, do people who discontinue their sport participation replace it with other forms of physical activity, or vice versa?

By applying BSEM[9] in this study, we were able to directly test *both* the conceptual sequence derived from the integration of the TPB[5] and BPN[14], and empirical expectations regarding the direction and strength of relations among study variables generated from statistical syntheses of research findings across multiple studies[7,8]. Our approach contrasts with previous research in which only the hypothesised conceptual sequence is tested[33,34]; that is, despite a wealth of available information regarding the empirical values for the structural relations, this prior knowledge is not incorporated into analyses when using traditional frequentist approaches such as linear regression or structural equation modelling with maximum-likelihood estimation. By drawing from meta-analytic data for informative priors, this Bayesian analysis is among the first to integrate prior research on TPB and BPN with new data and therefore empirically test the robustness of these empirical expectations.

Overall, our analyses revealed support for the robustness of the hypothesised theoretical model in terms of the pattern of relations as well as the direction and strength of associations among the constructs derived from quantitative summaries of existing research[7,8] and theoretical expectations[14,15]. A frequentist approach involves hypothetical repetitions of the study, with one's data representing the outcome from one real repetition, with an assumption that 95% of the hypothetical repetitions of the same sample size would produce an interval containing the true population parameter. Bayesian analysis provides an easily interpretable estimate in the form of a credibility interval for the unobserved population parameter[10]. For example, we can say with 95% certainty that the true parameter value linking behavioural intentions with sport continuation in our data is somewhere between .36

and .63. A comparison of the 95% credibility intervals generated with our data against those reported in previous statistical summaries[7] (which we used as prior knowledge) provide additional support for these established estimates, and therefore warrant further examination with other health-related behaviours (e.g., drinking, smoking, diet). For those researchers interested in sport continuation, the data presented here provide an important update to existing estimates (i.e., smaller range in the 95% credibility intervals) and therefore offer a foundation for future research.

Strengths of this study include the integration of two well-established theoretical frameworks for understanding sport continuation, consideration of multiple social agents, a homogenous sample of participants, inclusion of multiple referents for subjective norms and BPN, and application of innovative statistical analyses that integrated prior information and accounted for measurement error. Nevertheless, the study is not without limitation and these issues should be considered in future research. First, the contemporaneous assessment of all psycho-social variables at time one may have led to inflated estimates associated with common method bias. Temporally separating self-reported variables or obtaining assessments of study constructs from different sources (e.g., self, other, official records) can help alleviate such concerns. Second, although prospective designs such as the approach adopted in this study are useful in minimising bias from common methods, they are limited in their ability to support directional interpretations of structural relations in theoretical models; experimental manipulations of target variables (e.g., perceived behavioural control) would prove fruitful in drawing causal inferences among study variables. A third limitation relates to the use of a convenience sample of undergraduate students, which limits the robustness of the findings in terms of generalisations to other cohorts. Finally, there were some limitations with our measures. For example, our broad measure of ‘future intentions’ did not capture a specific time frame of 1-year and therefore may have biased our results. Additionally, we were unable to ascertain if those individuals who did not continue with their sport did so because of factors beyond their control (e.g., injury) or whether they switched to a different sport.

Conclusion

In summary, we provided support for an integrated theoretical model in which global perceptions of the social environment (BPN) influenced social-cognitive predictors (TPB) of sport continuation among young adults. Rather than ignoring prior knowledge regarding the direction and strength of relations from previous meta-analyses[7,8], BSEM enabled us to integrate these expectations with the current data to establish credible intervals for these estimates providing a direct test of existing research.

Practical Implications

- Interventions that increase an individual's perceived behavioural control and enhance positive attitudes toward organised sport may prove effective in promoting retention to organised sport.
- Educate adult leaders (e.g., coaches) and athletes about conditions and strategies that foster the satisfaction of BPN
- Efforts that target the architects of the social context (e.g., coaches) alongside its participants may be more effective than either approach in isolation

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Table 1. Survey items to capture the theories of planned behaviour and basic psychological needs.

Attitudes

"Continuing my participation in my main sport in the future would be..." [7-point semantic differential responses]]

1. Useless/useful
2. Boring/interesting
3. Worthless/valuable
4. Unpleasant/pleasant
5. Negative/positive
6. Uncomfortable/comfortable
7. Harmful/beneficial
8. Unenjoyable/enjoyable

Subjective Norms

1. My family/friends think it is important for me to continue my participation in my main sport ['totally disagree' to 'totally agree']
2. My family/friends approve of me continuing my participation in my main sport ['totally disagree' to 'totally agree']
3. My family/friends want me to continue participating in my main sport ['totally disagree' to 'totally agree']

Perceived Behavioural Control

1. How much control do you have over whether you continuing participating in your main sport in the future? ['very little control' to 'complete control']
2. For me to continue participating in my main sport in the future is... ['extremely difficult' to 'extremely easy']
3. I am confident that I could continue participating in my main sport in the future ['totally disagree' to 'totally agree']
4. Whether I continue participating in my main sport in the future is completely up to me ['totally disagree' to 'totally agree']

Intention

1. I intend on continuing to participate in my main sport in the future ['extremely unlikely' to 'extremely likely']
2. Will you continue to participate in your main sport in the future? ['definitely plan not to' to 'definitely plan to']

Basic Psychological Needs

Whilst thinking about *the peers* (e.g., other athletes, musicians)/*adult leaders* (e.g., coach, supervisor) you interact with in your main out-of-school activity, please respond to each statement by indicating how true it is for you at this point in time ['not at all true' to 'completely true']

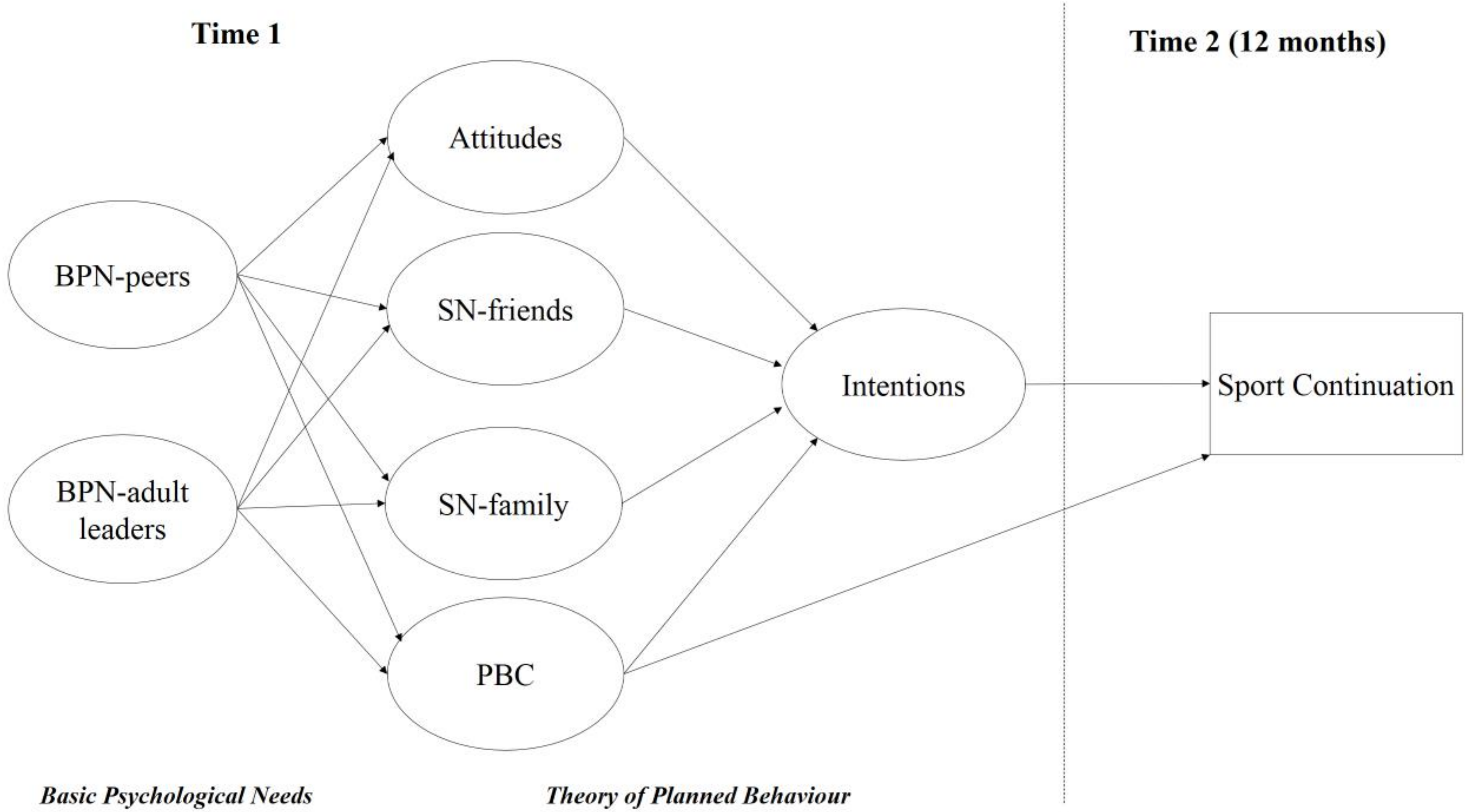
1. When I am with my peers/adult leaders, I feel free to be who I am
2. When I am with my peers/adult leaders, I feel like a competent person
3. When I am with my peers/adult leaders, I feel cared about
4. When I am with my peers/adult leaders, I often feel inadequate or incompetent (reversed-scored)
5. When I am with my peers/adult leaders, I have a say in what happens, and I can voice my opinion
6. When I am with my peers/adult leaders, I often feel a lot of distance in our relationship (reversed-scored)
7. When I am with my peers/adult leaders, I often feel very capable and effective
8. When I am with my peers/adult leaders, I feel a lot of closeness
9. When I am with my peers/adult leaders, I feel controlled and pressured to be certain ways (reversed-scored)

Table 2. Descriptive statistics, internal reliability estimates, effect sizes, and standardized weights of parameter estimates of Bayesian structural equation modelling (BSEM).

		M	*SD*	Skew	Kurtosis	1	2	3	4	5	6	7	8
1	BPN-a	4.72	1.04	-.05	-.45	(.88)	.51*	-	-	-	-	-	-
2	BPN-p	5.31	1.07	-.47	-.21	-	(.89)	-	-	-	-	-	-
3	Attitudes	5.89	1.12	-1.61	3.72	.25*	.28*	(.95)	.41*	.45*	.35*	-	-
4	PBC	5.97	.95	-1.38	2.17	.24*	.23*	-	(.75)	.39*	.27*	-	-
5	SN-peer	5.46	1.18	-.55	-.28	.25*	.23*	-	-	(.87)	.59*	-	-
6	SN-family	5.65	1.32	-.88	.09	.15*	.23*	-	-	-	(.91)	-	-
7	Intention	5.91	1.37	-1.60	2.46	-	-	.28*	.51*	.07	.02	(.95)	-
8	Continuation	($n_{dropout}$ = 65; $n_{continuation}$ = 227)				-	-	-	.23*	-	-	.50*	-
	R^2					-	-	.21	.17	.18	.11	.56	.46

Note: basic psychological needs from adult leaders (BPN-a); basic psychological needs from peers (BPN-p); perceived behavioural control (PBC); subjective forms from peers (SN-peers); subjective norms from family (SN-family); the amount of variance in a latent variable explained by its predictors (R^2); internal reliability estimates (Cronbach's alpha) provided on the diagonal in parentheses; BSEM parameter estimates are provided below the diagonal, whereas latent variable correlations are provided above the diagonal in grey shade; statistically significant loadings marked with an asterisk have a 95% credibility interval that does not encompass zero.

Figure 1. *Hypothesized theoretical integration of the theories of planned behaviour and basic psychological needs for sport continuation*. Note: latent variable correlations, item indicators and their error terms are not shown for parsimony; basic psychological needs from adult leaders (BPN-adult leaders); basic psychological needs from peers (BPN-peers); perceived behavioural control (PBC); subjective forms from peers (SN-peers); subjective norms from family (SN-family).



Supplementary Material

Appendix A – Additional Detail on Bayesian Analysis Specifications

In this section, we provide additional detail on the specifications we employed for the Bayesian analyses (see Table S1). Interested readers can contact the corresponding author for a copy of the complete Mplus input file. As can be seen in Table S1, we forced each Markov chain Monte Carlo (MCMC) procedure to iterate 100,000 times rather than the default Mplus formula based on the convergence criterion of .05[1]. This specification allowed us to examine the PSR development over iterations beyond the point at which Mplus deemed our model to converge. Although not reported here, there was a smooth decrease in the PSR value until 57000 iterations where it reached 1.05, at which point this value remained relatively stable over the last several thousand iterations[2]. An inspection of the trace plots revealed further support for model convergence; for example, as depicted in Figures S1 and S2 the two chains mixed well, with a stable posterior distribution. We employed the Mplus default of two independent chains of the MCMC procedure.

The "Model Priors" section is where the analyst specifies priors for the parameters of interest. With regard to the measurement model component, each intended factor loading and cross-loading is designated with a parameter label in the "Model" section so that one can subsequently associate each with priors. Below is an excerpt from the measurement model of the theory of planned behaviour concepts:

```
ATT BY att1* att2 att3 att4 att5 att6 att7 att8 (f1l1-f1l8)
peer_norm1 peer_norm2 peer_norm3 (xl1-xl3)
fam_norm1 fam_norm2 fam_norm3 (xl4-xl6)
pbc1 pbc2 pbc3 pbc4 (xl7-xl10);
ATT@1;
```

Here we can see that the intended factor loadings for the attitude (ATT) latent factor are labelled by f1l1-f1l8, whereas the cross-loadings are captured by the labels xl1-xl10. In the model priors section, we informed Mplus that the intended factor loadings and cross-loadings should have an approximately normal distribution (~N) with a mean of 0.7 and 0, respectively, and both with a variance of 0.02 (equating to a 95% limit of $\pm$ .28 around the mean). As shown below, a similar approach is adopted for naming the structural paths of the model:

```
ATT ON BPN_A (b7);
PBC ON BPN_A (b8);
SNpeer ON BPN_A (b9);
SNfam ON BPN_A (b10);
ATT ON BPN_P (b11);
PBC ON BPN_P (b12);
SNpeer ON BPN_P (b13);
SNfam ON BPN_P (b14);
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The priors for residual variances and their covariances draw from an inverse-Wishart (IW) distribution. This issue is complex and an informative discussion is well beyond the scope of this paper; interested readers should consult Muthén and Asparouhov (2012) for an introduction. Conveniently, Mplus provides information on the priors as part of the output file, such that one can examine the translation of the IW distribution into prior mean and variance. For example, our prior specification for residual variances (1, 44) translated into a mean of .20 with a variance of .027.

Appendix B – Testing Different Priors

As correctly noted by an anonymous reviewer, different priors can result in different results[3]. Accordingly, we performed a sensitivity analysis to compare the results of different prior specifications on key model parameters[4]. A sensitivity analysis is particularly important with smaller samples (relative to the number of parameters in the model) because prior specifications are more influential than with larger samples[3]. We considered three models for the purposes of our sensitivity analysis, namely (Model 1) the original model including *informative priors* based on meta-analytic evidence[5] and theoretical expectations[6,7]; (Model 2) an alternative version of our original model in which the variances around the expected parameter estimates were set to be *highly precise* (i.e., .001 or a 95% limit of $\pm$ .06 around the mean); and finally (Model 3) an *uninformative* model (i.e., Mplus defaults). An examination of the PSR development over iterations and inspection of trace plots indicated that all three models converged. An overview of the prior specifications for each of these models is depicted in Table S2. The results of the sensitivity analysis are detailed in Table S3.

The sensitivity analyses revealed that Model 3 was inadequate; that is, the data were improbable given the model (PPP = .000). An examination of the output revealed that 73% (i.e., 514 of 703) of the residual covariances were significant thereby indicating model misspecification. Model fit was substantially improved in both Models 1 and 2, which included informative priors for structural paths and residual co/variances. The parameter estimates of Model 2 were slightly stronger and accompanied by smaller 95% credibility intervals when compared with Model 1, with the exception of the paths from perceived behavioural to intentions and sport continuation. This finding is to be expected given that highly precise priors were set in Model 2. The deviance information criterion is an index that can be used to compare Bayesian models even when they are not nested[4]; however, the DIC is currently not available in Mplus when the model includes a binary endogenous variable. We consider the PPP as an alternative for ascertaining the quality of these two models. Specifically, the observed data fit better than the generated data almost 70% of the time in Model 1 (PPP = .685) compared with approximately 47% of the time for Model 2 (PPP = .473); in other words, Model 2 is almost just as probable as the generated data, whereas Model 1 is more probable than the generated data. Model 1 also better incorporates prior information derived from meta-analyses with our new data, thereby enabling us to provide an "automatic meta-analysis"[8].

Appendix C – Bayesian versus Maximum-Likelihood Estimation

Given that a key aim of this study was to demonstrate the usefulness of a Bayesian approach, some readers may be interested to know how the results compare with the findings of the traditional frequentist approach of maximum-likelihood (ML) estimation. In ML estimation, the parameter estimates are continuously refined through an iterative process until the discrepancy between the sample covariance matrix (i.e., data) and the implied covariance matrix (i.e., measurement and structural model) can no longer be reduced[9]; that is, the best model in ML estimation is the one that maximises the probability of the observed data. Within an ML framework, item cross-loadings (e.g., attitude items loaded solely on the attitude latent factor and not other constructs of the TPB) and residual covariances are fixed at zero. For the purposes of the current study, however, we modelled correlations among item residuals of subjective norms (family and peers) and basic psychological needs (adult leaders and peers) because they shared a common method factor in that the same item was employed for each construct except that target was altered in the instructional set (see Table 1). The results of the ML estimation procedure are detailed and compared with the findings of the Bayesian analysis of our original model in Table S4.

Overall, the results are numerically similar across Bayesian and ML estimation, although there are two minor differences. First, the paths from attitudes to intentions, and from basic psychological needs from adults to perceived family norms, are substantively important with Bayesian yet non-significant with ML estimation. Second, the strength of the path from perceived behavioural control to intentions is higher for ML when compared with Bayesian estimation.

Empirical differences aside, implementing Bayesian methods offers theoretical advantages over ML estimation[3]. First, with the traditional frequentist approach (e.g., ML-SEM), the data are assumed to be a random sample from the population and parameters are considered as quantities whose values are fixed but unknown[10]. Here, the researcher is interested in the probability of the data, given the hypothesised theoretical model; from a Bayesian perspective, one is interested in the probability of a hypothesised theoretical model, given the data.

Second, frequentist inference contrasts a null hypothesis with an alternative hypothesis in conjunction with confidence intervals to express a level of support that the true population parameter estimate is not the value under the null[10]. Within the context of structural equation modelling, for example, one is interested in evaluating support against the null hypothesis that there is no difference between the sample covariance matrix (i.e., data) and the implied covariance matrix (i.e., measurement model). As the frequentist approach involves the estimation of parameters based on hypothetical repetitions of the same study, the correct interpretation of the confidence interval is that 95% of these replications capture the fixed but unknown parameter[3]. In contrast, Bayesian analysis summarises one's prior knowledge in the probability distribution and integrates these expectations with the data's evidence about the parameters to generate the relative probability of different values[2]. Thus, whereas the frequentist perspective depends on data that were not observed in one's research, Bayesian analysis provides an easily interpretable estimate in the form of a credibility interval for the unobserved population parameter that lies between two values[3,10]. This approach allows for the updating of knowledge either through the replication, strengthening, or diversification of theoretical conclusions.

Table S1. Overview of Mplus specifications for Bayesian analysis (*Note*: text in green and preceded by an exclamation mark is not read by Mplus when executing the analysis).

```
ANALYSIS:
ESTIMATOR = BAYES;
FBITERATIONS = 100000; !sets a fixed number of iterations for each Markov chain Monte Carlo (MCMC) chain when Gelman-Rubin PSR is not used to determine convergence; when using this option, analysts need to manually check for convergence (e.g., PSR development over iterations, visual inspection of trace plots)
MODEL PRIORS:
!informative priors for measurement model parameters; below are the intended factor loadings where the mean is set at 0.7 and the variance is .02
   f1l1-f1l8~N(0.7,0.02);
   f2l1-f2l4~N(0.7,0.02);
   f3l1-f3l2~N(0.7,0.02);
   f4l1-f4l3~N(0.7,0.02);
   f5l1-f5l3~N(0.7,0.02);
   f6l1-f6l9~N(0.7,0.02);
   f7l1-f7l9~N(0.7,0.02);
!informative priors for measurement model parameters; below are the cross-loadings where the mean is set at 0 and the variance is .02
   xl1-xl72~N(0,0.02);
!informative priors for structural paths of the model
   b1~N(0.48,0.041);
   b2~N(0.26,0.019);
   b3~N(0.78,0.052);
   b4~N(0.72,0.046);
   b5~N(0.32,0.036);
   b6~N(0.32,0.036);
   b7-b14~N(0.4,0.02);
!priors for residual variances
   rv1-rv38~IW(1,44);
!priors for correlated residuals
   cr1-cr703~IW(0,44);
```

Table S2. Overview of priors employed for structural paths of Bayesian analysis.

	Model 1		Model 2		Model 3	
Parameters	μ	σ^2	μ	σ^2	μ	σ^2
Theoretically Informed						
BPN-a → ATT	.40	.02	.40	.001	.00	10^{10}
BPN-a → PBC	.40	.02	.40	.001	.00	10^{10}
BPN-a → SN-p	.40	.02	.40	.001	.00	10^{10}
BPN-a → SN-f	.40	.02	.40	.001	.00	10^{10}
BPN-p → ATT	.40	.02	.40	.001	.00	10^{10}
BPN-p → PBC	.40	.02	.40	.001	.00	10^{10}
BPN-p → SN-p	.40	.02	.40	.001	.00	10^{10}
BPN-p → SN-f	.40	.02	.40	.001	.00	10^{10}
Empirically Informed						
ATT → INT	.78	.052	.78	.001	.00	10^{10}
PBC → INT	.72	.046	.72	.001	.00	10^{10}
SN-p → INT	.32	.036	.32	.001	.00	10^{10}
SN-f → INT	.32	.036	.32	.001	.00	10^{10}
INT → BEH	.48	.041	.48	.001	.00	10^{10}
PBC → BEH	.26	.019	.26	.001	.00	10^{10}

Note: μ = mean; σ^2 = variance; basic psychological needs from adult leaders (BPN-a); basic psychological needs from peers (BPN-p); attitudes (ATT); perceived behavioural control (PBC); subjective forms from peers (SN-p); subjective norms from family (SN-f); intention (INT); sport continuation (BEH); posterior predictive p value (PPP). Model 1 = originally hypothesised model; Model 2 = variance around the expected parameter estimates of original model was set to be *highly precise* (i.e., .001 or a 95% limit of $\pm$ .06 around the mean); and Model 3 = uninformative prior distribution reflecting no prior knowledge (i.e., default settings in Mplus for structural components only).

Table S3. Comparison of standardised weights of parameter estimates and model fit of Bayesian structural equation modelling (BSEM) using different priors.

	Model 1		**Model 2**		**Model 3**	
Parameters	μ	95% CI	μ	95% CI	μ	95% CI
BPN-a → ATT	.25*	.14, .35	.32*	.28, .36	.14	-.28, .51
BPN-a → PBC	.24*	.12, .34	.31*	.27, .36	.11	-.26, .48
BPN-a → SN-p	.25*	.14, .35	.33*	.29, .37	.14	-.32, .56
BPN-a → SN-f	.15*	.03, .27	.31*	.26, .35	.06	-.44, .55
BPN-p → ATT	.28*	.17, .37	.32*	.28, .37	.16	-.24, .58
BPN-p → PBC	.24*	.12, .34	.31*	.26, .35	.11	-.27, .47
BPN-p → SN-p	.23*	.12, .34	.32*	.28, .36	.08	-.37, .50
BPN-p → SN-f	.23*	.11, .33	.32*	.27, .36	.10	-.40, .56
ATT → INT	.29*	.14, .43	.41*	.38, .44	.34	-.14, .71
PBC → INT	.51*	.38, .63	.39*	.36, .42	.47*	.07, .85
SN-p → INT	.07	-.09, .22	.15*	.12, .18	.10	-.31, .51
SN-f → INT	.02	-.14, .17	.15*	.11, .18	.06	-.34, .47
INT → BEH	.50*	.35, .63	.62*	.57, .66	.74*	.32, 1.11
PBC → BEH	.23*	.10, .36	.19*	.15, .23	.26	-.23, .65
ATT ↔ PBC	.41*	.18, 59	.25*	.05, .42	.47*	.07, .79
ATT ↔ SN-p	.45*	.23, .62	.39*	.20, .55	.37	-.20, .79
ATT ↔ SN-f	.35*	.14, .52	.36*	.18, .51	.31	-.27, .77
PBC ↔ SN-p	.39*	.12, 60	.24*	.02, .44	.34	-.24, .74
PBC ↔ SN-f	.27*	.00, .51	.19	-.03, .40	.24	-.30, .70
SN-p ↔ SN-f	.59*	.41, .73	.65*	.50, .77	.35	-.28, .79
BPN-a ↔ BPN-p	.51*	.35, .64	.31*	.13, .47	.43*	.06, .82
Model Fit						
PPP	.685		.473		.000	
Δobserved and replicated χ^2	-142.62, 87.89		-109.92, 119.79		125.51, 399.43	

Note: basic psychological needs from adult leaders (BPN-a); basic psychological needs from peers (BPN-p); attitudes (ATT); perceived behavioural control (PBC); subjective forms from peers (SN-p); subjective norms from family (SN-f); intention (INT); sport continuation (BEH); posterior predictive p value (PPP). Model 1 = originally hypothesised model; Model 2 = variance around the expected parameter estimates of original model was set to be *highly precise* (i.e., .001 or a 95% limit of ± .06 around the mean); and Model 3 = uninformative prior distribution reflecting no prior knowledge (i.e., default settings in Mplus for structural components only).

Table S4. Comparison of frequentist analysis (maximum likelihood structural equation modelling [ML-SEM]) with Bayesian structural equation modelling (BSEM).

		Bayesian Analysis (BSEM)							
		1	2	3	4	5	6	7	8
1	BPN-a	(.88)	.51*	-	-	-	-	-	-
2	BPN-p	-	(.89)	-	-	-	-	-	-
3	Attitudes	.25*	.28*	(.95)	.41*	.45*	.35*	-	-
4	PBC	.24*	.23*	-	(.75)	.39*	.27*	-	-
5	SN-peer	.25*	.23*	-	-	(.87)	.59*	-	-
6	SN-family	.15*	.23*	-	-	-	(.91)	-	-
7	Intention	-	-	.28*	.51*	.07	.02	(.95)	-
8	Continuation	-	-	-	.23*	-	-	.50*	-
	R^2	-	-	.21	.17	.18	.11	.56	.46

		Frequentist Analysis (ML-SEM)							
		1	2	3	4	5	6	7	8
1	BPN-a	(.88)	.59*	-	-	-	-	-	-
2	BPN-p	-	(.89)	-	-	-	-	-	-
3	Attitudes	.26***	.27***	(.95)	.50***	.44***	.33***	-	-
4	PBC	.24**	.24**	-	(.75)	.44***	.35***	-	-
5	SN-peer	.20*	.23**	-	-	(.87)	.57*	-	-
6	SN-family	.12	.19*	-	-	-	(.91)	-	-
7	Intention	-	-	.14	.62***	.06	.01	(.95)	-
8	Continuation	-	-	-	1.52#	-	-	2.47#	-
	R^2	-	-	.19	.15	.15	.08	.56	.48

Note: basic psychological needs from adult leaders (BPN-a); basic psychological needs from peers (BPN-p); perceived behavioural control (PBC); subjective forms from peers (SN-peers); subjective norms from family (SN-family); the amount of variance in a latent variable explained by its predictors (R^2); internal reliability estimates (Cronbach's alpha) provided on the diagonal in parentheses; BSEM parameter estimates are provided below the diagonal, whereas latent variable correlations are provided above the diagonal in grey shade; for BSEM, statistically significant loadings marked with an asterisk have a 95% credibility interval that does not encompass zero; for ML-SEM, * p <.05, ** p <.01, *** p <.001; # logistic regression odds ratio.

Figure S1. Two chains specified for the Gibbs sampler of the regression of sport continuation on intention.

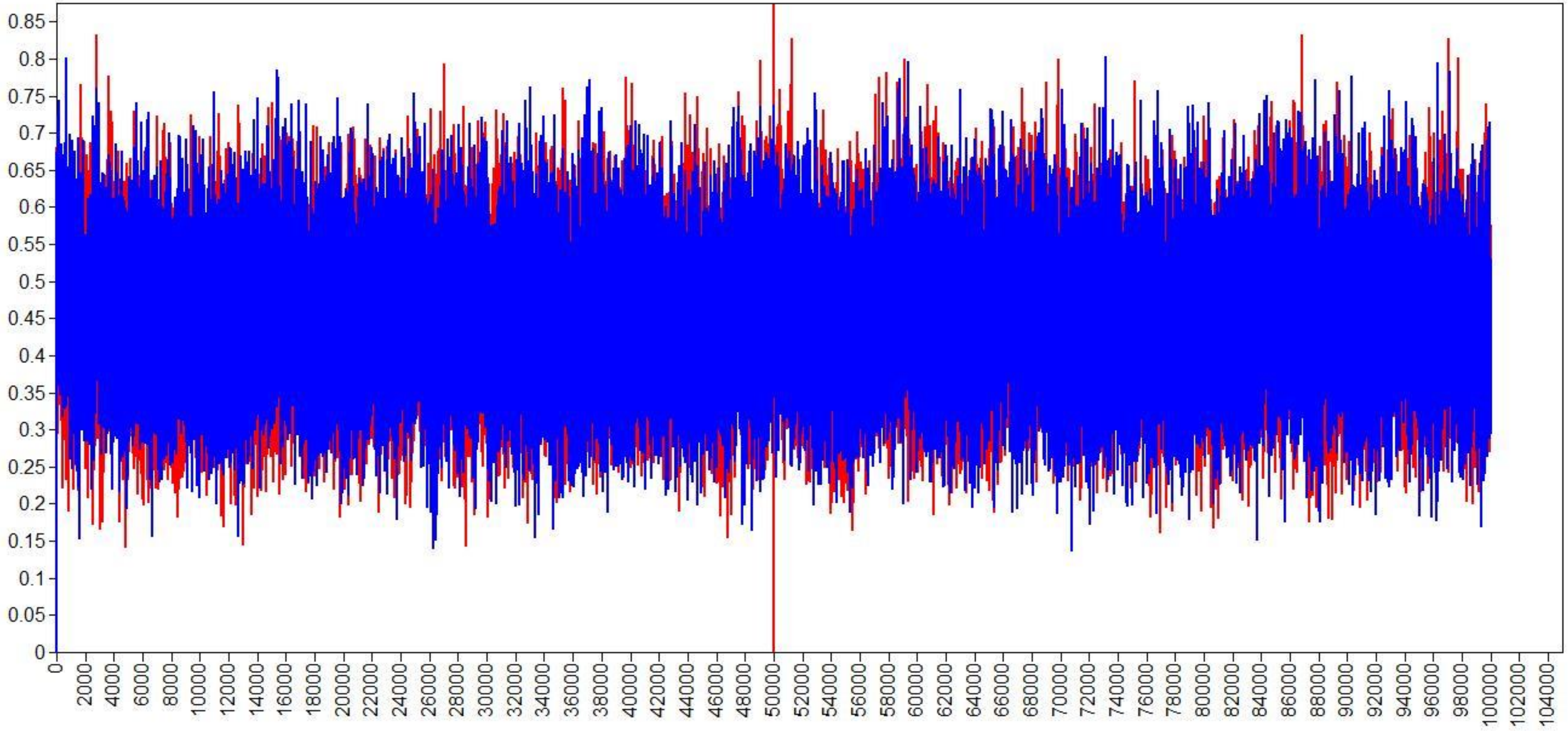
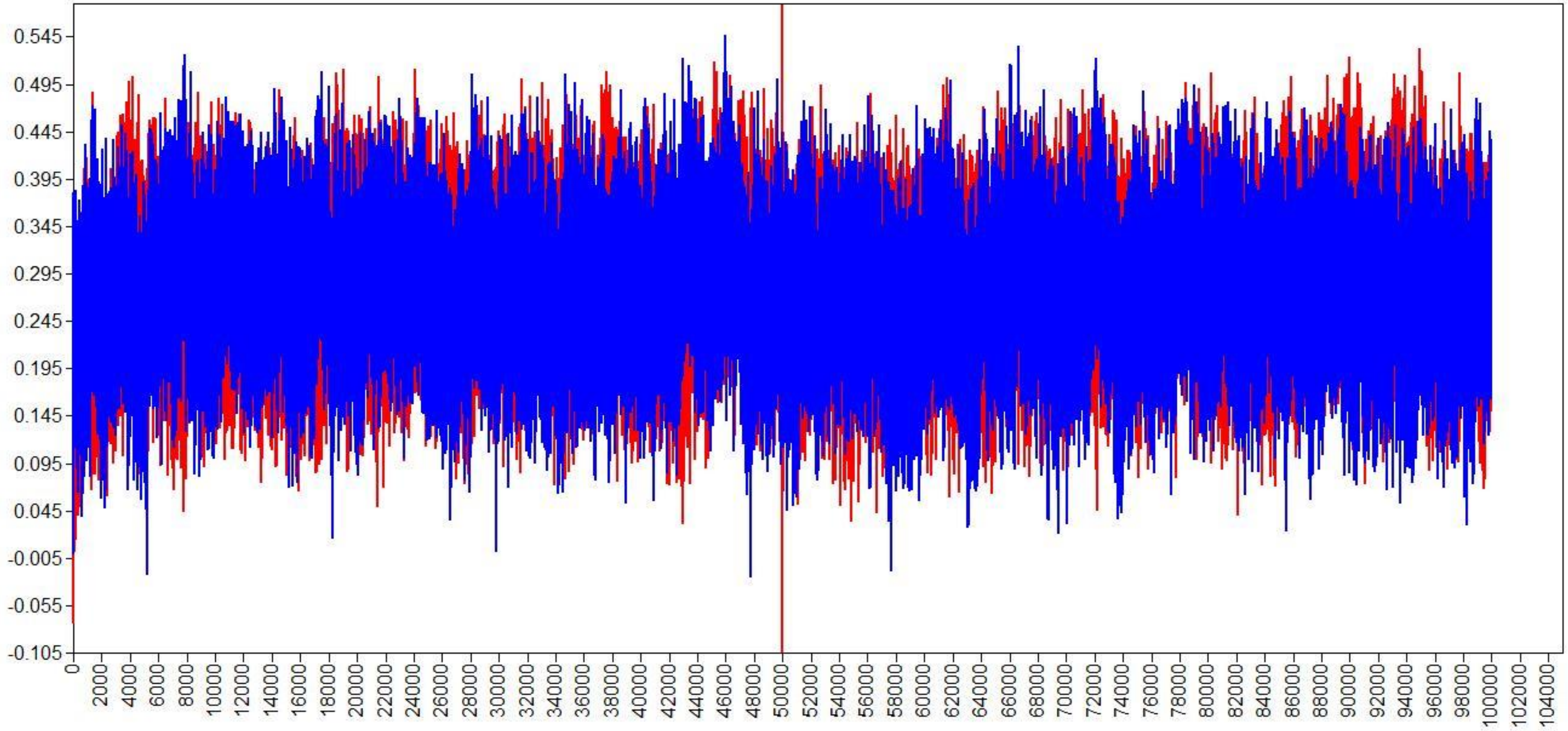


Figure S2. Two chains specified for the Gibbs sampler of the regression of attitudes on basic psychological needs from adults.



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