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Sense of direction and conscientiousness as predictors of performance in the Euclidean travelling salesman problem

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Abstract

A salesperson wishes to visit a number of cities before returning home using the shortest possible route, whilst only visiting each city once. This optimization problem, called the Travelling Salesman Problem, is difficult to solve using exhaustive algorithms due to the exponential growth in the number of possible solutions. Interestingly, when presented in Euclidean space (ETSP), humans quickly find good solutions. Past studies, however, are in disagreement whether human solutions are impacted by the participant's ability to process figural effects in the graph geometry. In this study, we used principal component analysis to combine two correlated [$r = 0.37$, $p < 0.01$] self-assessed personality measures, i.e., a participant's sense of direction and a participant's level of conscientiousness, onto a single impulsiveness/cautiousness dimension. We then showed, using simple linear regression, that this new dimension is a significant predictor [$R^2 = 0.12$, $p < 0.01$] of the number of edge crossings that occur in human ETSP solutions, a key metric of graph optimality. Our study provides evidence to suggest

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that human solutions to the ETSP are significantly affected by individual differences, including personality and cognitive traits.

Keyword: Psychology

1. Introduction

In 1962, Procter and Gamble offered US$10,000 to whomever identified the shortest route through 33 U.S. cities, starting and finishing in the city of Chicago. This problem has 1.32×10^{35} possible routes, expressed as *(n-1)!/2;* where n is the number of cities. The computers of the day could process 10,000 routes per second, which meant, at an undefinable cost, it would take one machine 417 billion trillion years to analyse all possible routes (Applegate et al., 2007). These nondeterministic polynomial hard (NP-hard) problems occur in a wide range of industrial domains, including genome sequencing (Agarwala et al., 2000), analysis of crystal structures in X-ray diffraction (Bland and Shallcross, 1987), logistics (Dallari et al., 2000), the selection of routes for e.g., school buses and delivery of meals to the elderly (Schrijver, 2003), computer wiring, etc. (for an overview of applications, see Matai et al., 2010; MacGregor and Chu, 2011).

Despite the TSP being computationally immense, when nodes and routes are presented in 2D Euclidean space (i.e. ETSP), humans find good solutions in a close-to-linear time (Gärling, 1989; Dry et al., 2012). By creating a visuospatial reasoning task, even complex ETSP graphs can be solved effortlessly by humans; who provide near optimum solutions with limited planning and/or preparation (MacGregor and Ormerod, 1996). Even though the solving of hard problems is of significant research importance, with polynomial vs. nondeterministic polynomial highlighted by the Clay Mathematics Institute (CMI) as a millennium problem (CMI, 2016), understanding and reproducing low complexity 'close-to-optimal' alternatives is of considerable commercial value (Applegate et al., 2007).

1.1. ETSP cognitive heuristics

Literature concerning human performance, when solving ETSPs, highlights numerous global-to-local and local-to-global heuristics, which are used to identify near-optimal solutions. The *convex hull hypothesis* (MacGregor and Ormerod, 1996), for example, describes the formation of an imaginary perimeter around the boundary nodes (see Fig. 1), after which internal nodes are sequentially inserted on the tour path; in either a clockwise or counter clockwise direction, suggesting a global-to-local perceptual organizing process.

Graham et al. (2000) suggest an alternative, the *"pyramid model"*, which applies a local-to-global approach, and has been used extensively in computer and human vision literature; with developments mimicking peripheral and central human vision

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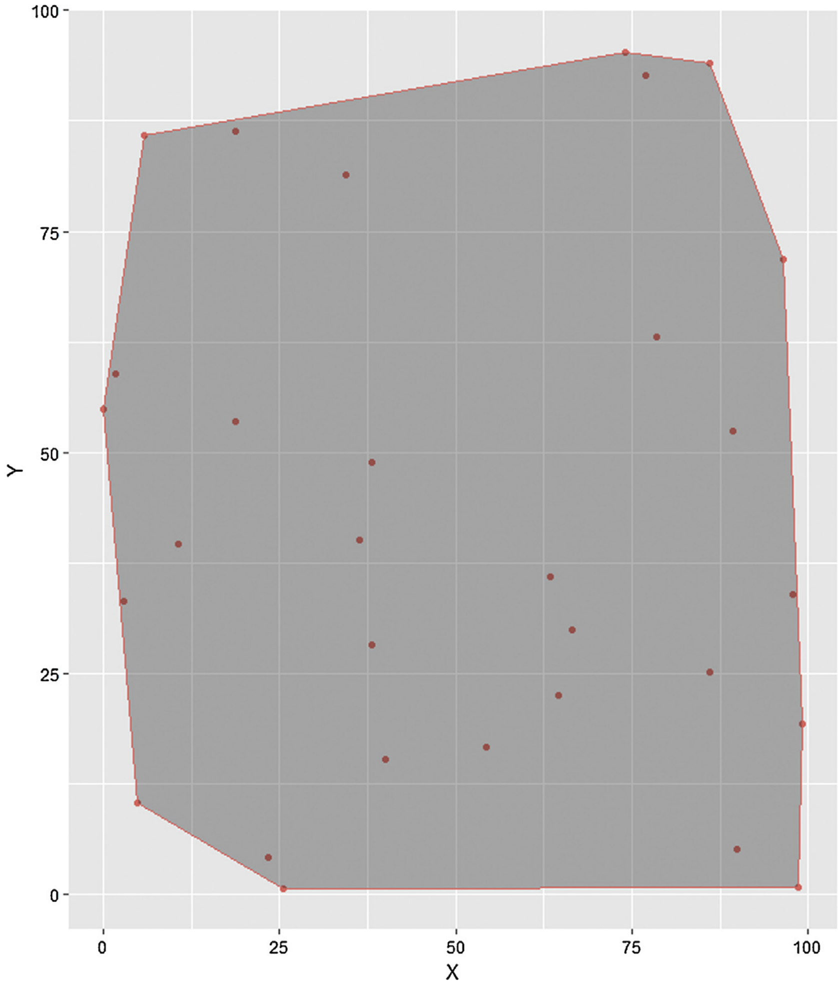

Fig. 1. The points required to form a shape around all points (grey area) is the convex hull of a graph. Distance is in arbitrary units.

(Pizlo et al., 2006). The pyramid model uses coarse-to-fine hierarchical clustering to simplify tour approximations. By using a bottom-up clustering process to group nodes (with no more than three nodes per group), each high-level problem becomes simpler as a result of the reduction in the number of child groups.

Both global-to-local and local-to-global theorists highlight, however, the importance of actively avoiding route crossings (Graham et al., 2000; MacGregor and Ormerod, 1996) – a concept termed the *crossing-avoidance hypothesis* by van Rooij et al. (2003).

1.2. Rule-based behavior and future goals in ETSP performance

The crossing avoidance hypothesis argues that people, when finding the shortest route between nodes, actively try to avoid crossing their own path. van Rooij et al.

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(2003) found crossing avoidance violations (see Fig. 2) in just 6% of participant solutions, suggesting that the crossing avoidance hypothesis is important to human performance when solving complex ETSP graphs. Even though there is an open discussion concerning how heuristics are used, all researchers agree that cross-avoidance minimizes tour costs (Flood, 1956). Fig. 2 provides an example of an ETSP graph with crossing violations (cost: 509.03) and without crossing violations (cost: 496.75).

Research concerning human solution strategies has focused on i) understanding the underlying heuristics used by humans to solve the ETSP, and ii) appreciation whether innate human abilities contribute to certain individuals being more likely to define optimal ETSP solutions. Some of the early work, such as that by MacGregor and Ormerod (1996), did not find any significant difference between the performance of participants, which led to the proposition that human solution strategy is influenced by low-level perceptual processes. This school of thought (MacGregor and Ormerod, 1996; Chronicle et al., 2006) reported no evidence of individual differences in ETSP performance.

Vickers et al. (2001), Vickers et al. (2004), however, reported a correlation between scores on the Raven's Advanced Progressive Matrices (a nonverbal test of fluid intelligence) and ETSP performance; implying a relationship between ETSP performance and individual differences. Miyata et al. (2014) compared TSP performance results between children and adults, to determine whether the crossing

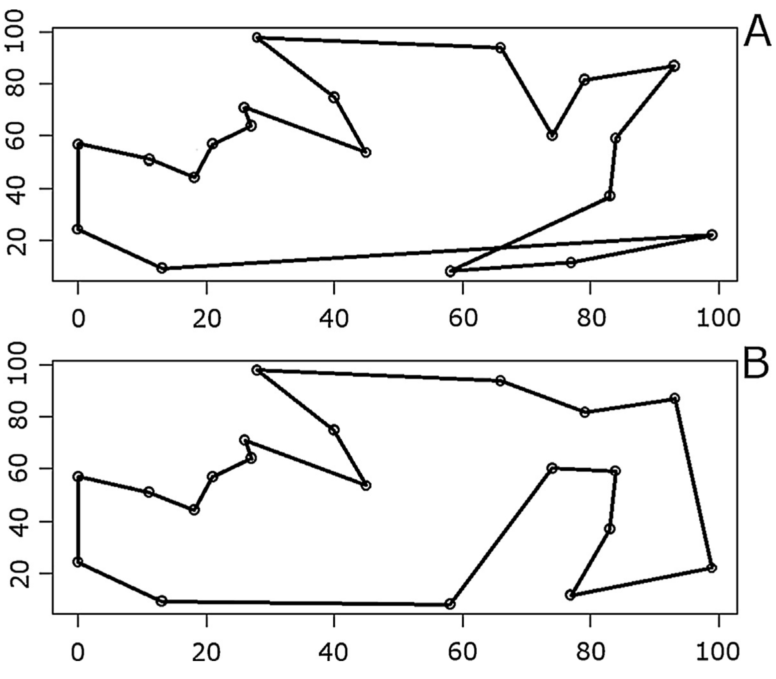

Fig. 2. ETSP graph with (A) and without (B) crossing avoidance violations. Distance is in arbitrary units.

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avoidance violation is linked to higher-level cognition, and showed that optimization task strategies are developed over time; implying that cross avoidance is learnt as a result of training, and/or experience in the real world.

Chronicle et al. (2008) also argued that individual differences become more significant as the graph complexity increases. This claim is supported by van Rooij et al. (2006) and Burns et al. (2006). van Rooij et al. (2006) reported that children (7–12 years old) perform well for low-node TSP graphs (i.e., 5, 10 and 15 nodes), which primarily utilizes perceptual processes, however adults perform significantly better for high-node TSP graphs, which require complex cognitive analytic processes. Burns et al. (2006) argued for the existence of individual difference in TSP performance with respect to both low level perceptual abilities (spatial relations) and high level perceptual abilities (verbal analytic reasoning). Using structural equation modeling, the authors showed that as the task becomes more difficult, both factors become significant predictors of TSP performance.

Non-human animals, such as pigeons, rats, and slime mold, produce good solutions using a simple *nearest neighbor (NN) approach*. Use of a NN approach to solve ETSP graphs, however, often results in inclusion of crossing violations (see Fig. 3), implying suboptimal route costs. Due to the low percentage of crossing violations in human solutions, it is reasonable to assume that planned behavior is present in humans.

1.3. Link between sense of direction and the solving of the ETSP

Blaser and Wilber (2013) indicated that humans employ slightly different ETSP strategies in figural and navigational environments. Individuals were found to focus on local strategies when performing in a figural environment, due to the clear

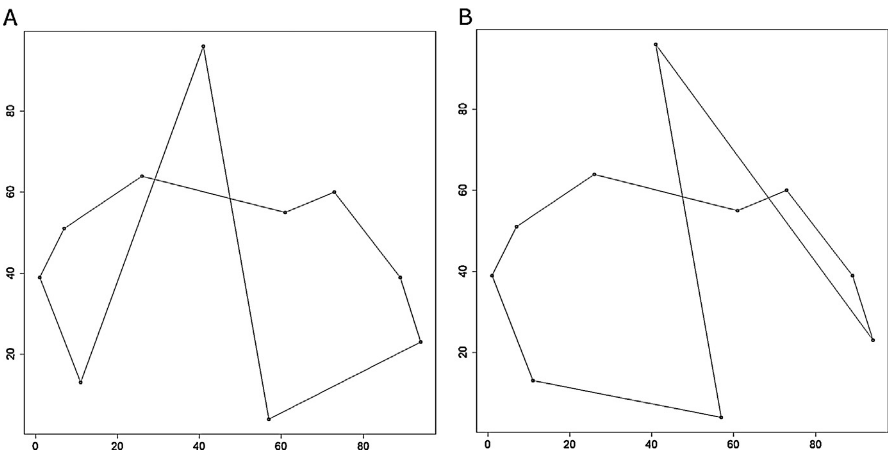

Fig. 3. Nearest Neighbour approach using the R library by Hahsler and Hornik (2007). Note that the route is impacted significantly by the coordinates of the starting city: A(57,4), B(94,23). Distance is in arbitrary units.

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global perspective. On the other hand, global strategies where more used in a navigational environment, due to a need to contextualize the physical location. Whatever the focus, results indicate a relationship between the environment, the search strategy, and the solution provided by specific user segments.

Wolbers and Hegarty (2010) used structural equation modelling to show that Spatial Ability (SA) correlated with an individual's self-reported Sense Of Direction (SOD). Moreover, both SA and SOD were found to be significant predictors of spatial learning, i.e., both via video and/or within a virtual environment. Interestingly, Condon et al. (2015) showed that some of the variance in SOD scores can be explained by participant conscientiousness. Conscientiousness is the human tendency to plan ahead and think with caution before acting on a given task (John et al., 2008), and relates to rule-based behavior and long-term planning. If conscientiousness is an indicator of long-term planning behavior, then we can hypothesize that an increase in impulsiveness, i.e. a decrease in conscientiousness, will correlate with a reduction in participant SA and SOD. This hypothesis is neurologically supported, since conscientiousness has been shown to be associated with the lateral prefrontal cortex (DeYoung et al., 2010), a brain region that, in the context of optimization problems, takes a supervisory role in pathfinding (Ahmadi-Pajouh et al., 2007). Moreover, Forbes et al. (2014) used voxel-based lesion-symptom mapping analysis to show that damage to the left dorsolateral prefrontal cortex (dlPFC) resulted in decreased conscientiousness scores; confirmed by research assessing ‘impulsivity’. For example, Borderline Personality Disorder (BPD) patients regularly have anomalies in both PFC and/or hippocampal regions of the brain (Brambilla et al., 2004; Sala et al., 2011).

1.4. Current study

This web-based experiment required participants to solve ETSP graphs online. The experiment considered occurrence of crossing-avoidance violations, i.e., solutions containing crossed edges, as a measure of ETSP performance. In this study we were interested in whether conscientiousness correlates to variance in SOD scores, as suggested by Condon et al. (2015). Moreover, using Principal Component Analysis, we were interested in whether a formed dimension could be used to predict the occurrence of a cross-avoidance violation; which is a strong indicator of graph optimality.

2. Materials and methods

2.1. Participants

A total of 101 participants (73 females and 28 males) were recruited. 55% of participants were between ages 18–24, 35% of participants were between ages 25–32, 7% of participants were between ages 33–40, 3% of participants were

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between ages 41–50 and 1% of participants were over 51. All participants indicated normal or corrected-to-normal vision. The participant pool was made up of BSc and MSc Psychology students. Ethical approval was obtained from the Cardiff Metropolitan University psychology department ethics committee, as well as the City Unity College ethics committee. All the procedures comply with the 1975Helsinki declaration and its later amendments. Informed consent was obtained from all individual participants included in the study using online consent forms, which worked as a pre-requisite to participating in our web-based experiment.

2.2. Materials

The online ETSP experimental platform front-end (i.e., the web-page with which participants interacted) was coded using Javascript and HTML5; whilst PHP and mySQL were used for back-end development. The experimental platform was tested in both Firefox and Google Chrome, and participants were asked to use these browsers. All data was initially captured in the database and later exported to .csv files for further analysis. The data was analysed using R (R Core Team, 2016). To assess participant conscientiousness scores, participants completed Goldberg's (Goldberg, 1992) 50-item Big-Five Factor Markers, taken from the International Personality Item Pool (IPIP, 2015). Goldberg’s inventory is one of the most widely used personality assessment instruments, showing high convergent validity with other personality inventories, such as the NEO Personality Inventory (NEO-PI; Costa and MacCrae, 1992). The inventory consists of 50 items, with 10 items measuring each of the Big Five personality factors, i.e. extraversion, agreeableness, conscientiousness, emotional stability, and intellect. Each item is composed of a short statement, such as, e.g., “I keep in the background”, “I often feel blue”. For every item, each participant is asked to indicate their level of agreement on a Likert scale; where 1 represents very accurate, and 5 represents very inaccurate. Goldberg's 50-item Big-Five has high internal consistency, with validation studies producing results ranging from: $\alpha = .74–.90$ (median $\alpha = .89$) for extraversion; $\alpha = .78–.85$ (median $\alpha = .83$) for agreeableness; $\alpha = .79–.89$ (median $\alpha = .80$) for conscientiousness; $\alpha = .80–.93$ (median $\alpha = .88$) for neuroticism; and $\alpha = .78 - .90$ (median $\alpha = .85$) for openness (see e.g., Ehrhart et al., 2008; Goldberg, 1999).

To assess sense of direction, the Santa Barbara Sense of Direction scale (SBSOD) was used (Hegarty et al., 2002), which requires participants to rate, on a scale of 1–7 (strongly agree to strongly disagree), a series of 15 items relating to their subjective perceptions of their navigational abilities (e.g., “I am very good at giving directions”, “I have a poor memory of where I left things”). Several studies indicate strong internal consistency ($\alpha = .88$), reliability (test-retest reliability = .91) and convergent validity with spatial skills measures for the SBSOD instrument (see Schinazi et al., 2013). Both self-reported tests were converted into an online presentation format and administered via Google Forms. To assess participant

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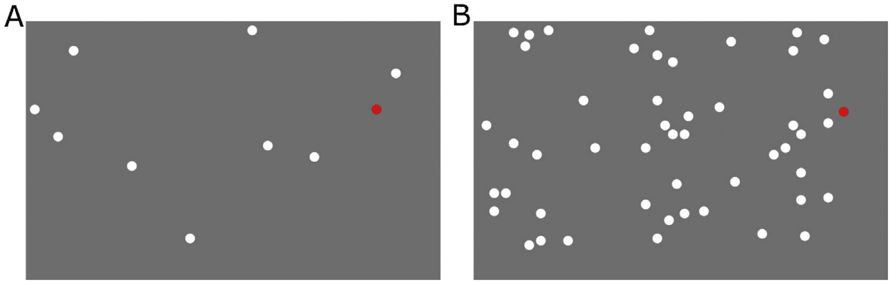

Fig. 4. Example of a trial with 10 nodes (A) and 50 nodes (B) as they appeared in the experiment. Red node represents start/end node.

ETSP performance, 15 graphs were randomly generated using R, which were subsequently copied into our JavaScript program. Five graph groups were created, with groups defined by the number of nodes in the graphs {i.e., 10, 20, 30, 40, and 50} (see Fig. 4). In each group there were three graph instances.

2.3. Procedure

The whole experimental procedure was conducted online, with participants being sequentially guided through different stages of the experiment. When entering the web-page, participants were initially asked to read the information sheet and provide ethical consent by typing their initials. Once ethical consent was confirmed, a page was displayed to the participants providing full instructions on how to complete the ETSP task. Participants were instructed to create the shortest possible route passing through all the nodes, eventually returning to the starting node. Once participants confirmed that they had understood the instructions, they were provided with an external link in order to complete the ETSP task. Each participant completed the same 15 ETSP trials, with the starting node indicated in red. Lines were automatically rendered as participants clicked from one node to the next, to illustrate a defined route. Once the node had been selected the color was changed to green (see Fig. 5). The software prohibited participants from re-visiting a node, i.e., by simply not registering the click. When clicking on the last white node, the page automatically completed and displayed the trial tour, and subsequently loaded the next trial until all 15 trials had been completed. The order of trials was random to remove any chance of order effects. Finally, the starting nodes were always the same for each participant, as past research indicates that starting from a more central location may increase the probability of crossings occurring (MacGregor, 2014). The procedure has been summarized in Fig. 6.

After completion of all trials, a random ID generator provided each participant with a unique number. Participants then completed a google form, which included demographic data (i.e., gender and age group), the 50-item Big-Five Factor

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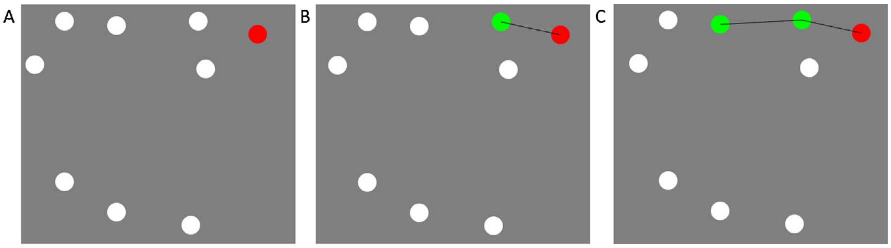

Fig. 5. Graphs would start off with a red node as the starting 'city' (A). The software responded to clicks by drawing routes between nodes (B), and colouring already selected nodes as green (C).

Markers test, and the Santa Barbara Sense of Direction instrument. Participants were asked to copy and paste their unique ID into the Google Form to allow us to link demographic data with ETSP, self-reported conscientiousness, and spatial navigation measurements.

3. Results

Total tour cost for each trial was calculated by taking the sum of distances between linked nodes, where C is the total route cost, x is a x-position cartesian coordinate vector, y is a y-position cartesian coordinate vector coordinates, and i is the current node, such that:

$$C = \sum_{i=1}^{n-1} \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2}$$

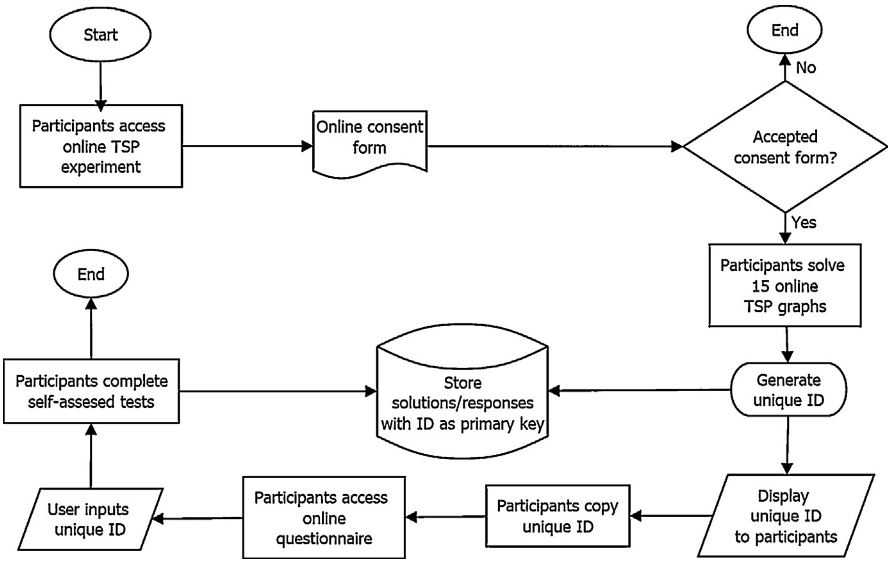

Fig. 6. The Flow chart summarises the experimental procedure. Upon completion of the TSP experiment, participants were asked to copy and then paste the unique ID into the online questionnaire. The id was then used to match the results from the ETSP to the questionnaire results for further analysis.

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Identification of crossing-avoidance errors was highlighted manually for each trial, and the data was marked with either a “1”, to represent the existence of one or more crossing-avoidance errors, or a “0”, to represent inclusion of no error. Mean number of crossing-avoidance violation errors, and mean route costs, were calculated for each participant.

Results of our study showed large discrepancies amongst participants with respect to route costs (min = 471.96, max = 860.07, *mean* = 516.17, *standard deviation* = 48.85) and number of trials that contain crossing-avoidance violations (min = 0%, max = 93%, *mean* = 27%, *standard deviation* = 25%). There was a strong, positive and significant correlation between route costs and crossing-avoidance violation errors, $r = 0.67$, $p < 0.01$, an expected result, as graphs with intersections are generally less optimal. Interestingly when the difference between the average number of errors between graphs (from 10 to 50) was plotted, no significant difference was identified in the means (Fig. 7).

3.1. The relationship between sense of direction and conscientiousness

QQ-plots and the Shaprio-Wilk tests were used to assess whether the scores from the self-reported tests followed the normal distribution. We found that in both cases normality assumptions were not violated, with the Shapiro-Wilk test returning $W = 0.99$, $p = 0.68$ for conscientiousness (CON), and $W = 0.99$, $p = 0.36$ for sense

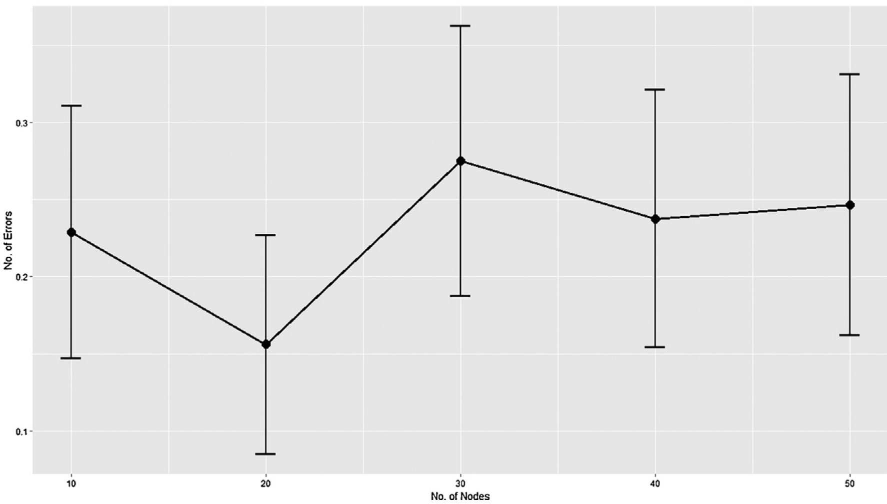

Fig. 7. Graph shows the mean number of crossing-avoidance violations (Errors) against total number of nodes across all trials (Error bars are 95% CI).

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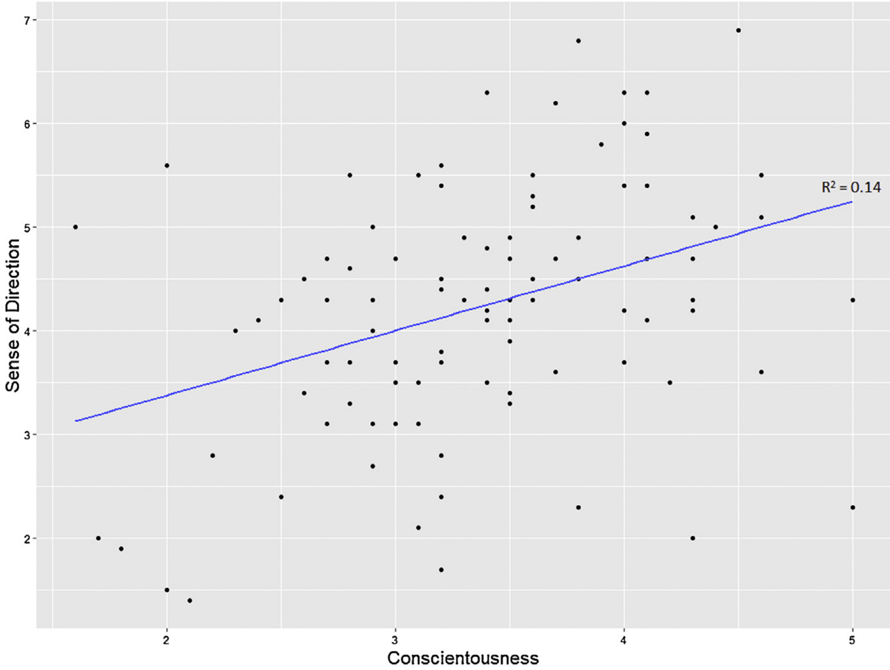

Fig. 8. Scatterplot and regression line shows the relationship between CON and SOD scores.

of direction (SOD). The two scores were found to be moderately correlated, $r = 0.37$, $p < 0.01$, using Pearson's r (Fig. 8).

Using Principal Component Analysis (PCA) with varimax rotation, CON and SOD were combined into a single component, coined the impulsiveness vs cautiousness (*IMP*) dimension. Pre-analysis measures were used to ensure that our experimental data satisfies criteria required to perform PCA. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy equaled 0.5, an acceptable level to support factor analysis. Bartlett's test of sphericity was significant ($p < 0.05$), which supports use of PCA. With an eigenvalue of 1.37, factor loadings for CON and SOD variables was 0.83. The average proportion of the variance explained by the factors for each item (i.e., the communalities) was 68%, greater than the 50% required for sample sizes less than 300 (Field, 2009).

3.2 Modelling the relationship between impulsiveness and cross-avoidance violations

Having reduced the CON and SOD scores into a single Impulsiveness vs Cautiousness (*IMP*) dimension, using PCA, we examined whether this dimension can predict the probability of crossing-avoidance violations (*Errors*) occurring in human solutions. A generalized linear model in the form of a simple linear regression was used with *IMP* as the independent variable, and *Errors* as the dependent variable (see Table 1). The relationship between the variables was found

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Table 1. Coefficients of the simple linear regression.

	Estimate	Standard Error	t value	p-value
Intercept	2.45	0.24	10.13	<0.005
Impulsiveness	0.22	0.06	3.94	<0.005

to be significant, with the model accounting for a small amount of the variance [R^2 = 0.12] (see Fig. 9).

Model diagnostics were used to validate our model (see Fig. 10). QQ plots indicate that the residuals from the linear model were fairly normal. Furthermore, in order to test homoscedasticity, i.e. the assumption that variance around the regression line is the same for all values of the predictor variable, the standardised residuals were plotted against predicted values. The output indicated fairly consistent variability for all predicted values, supporting the homoscedasticity assumption, and giving us confidence in the results of our regression model. Finally, post-hoc power analysis indicated that for simple bivariate linear regression, a minimum sample size of 71 participants is required in order to obtain a statistical power of 0.8 (i.e., 80% chance to find an effect when one exists). Therefore, our sample size of 101 was sufficient for this study.

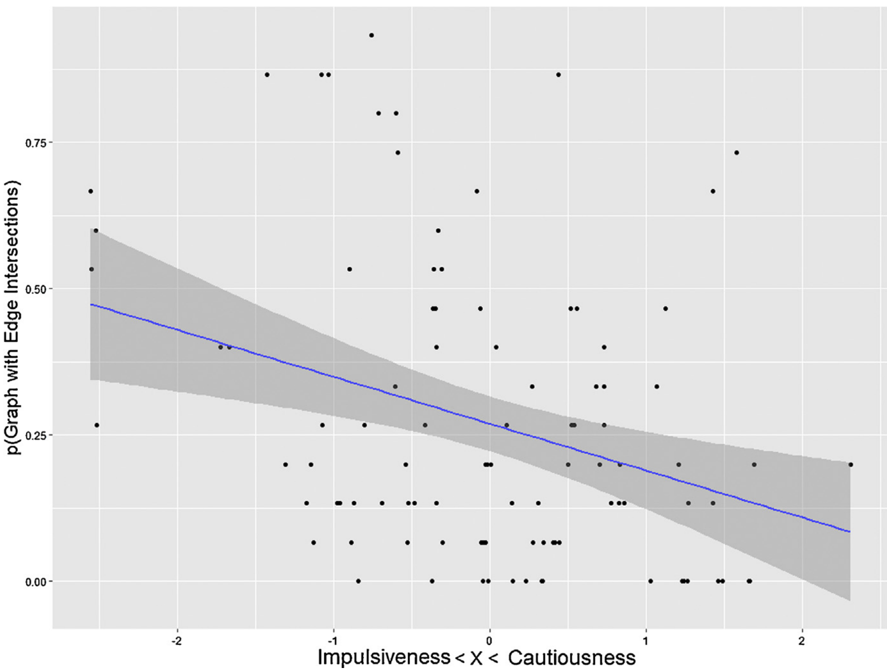

Fig. 9. A simple linear regression was used to predict the probability of crossings occurring in human solutions based on the component scores from the PCA (which we hypothesise to be a form of Impulsiveness). Shaded area is 95% confidence level interval for predictions.

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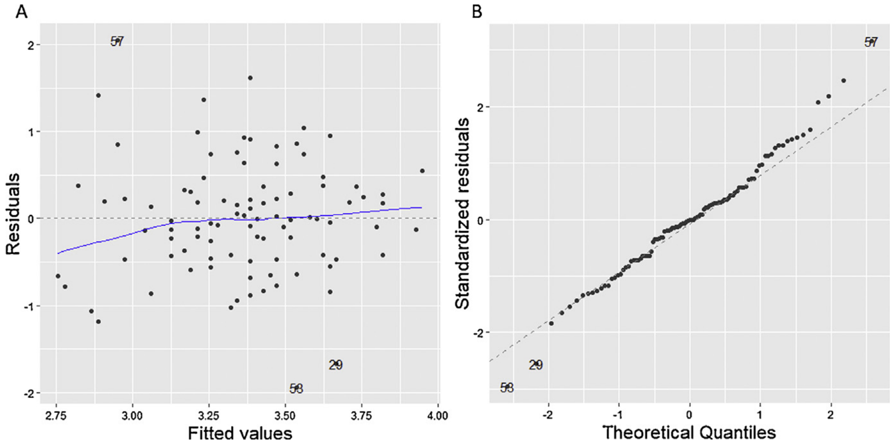

Fig. 10. QQplot of standardized residuals appears fairly normal (A). The scatterplot of residual vs fitted points indicates random spread, supporting homoscedasticity (B).

4. Discussion

In this study we hypothesized that self-reported measures of spatial cognition and organisation can be used to predict some of the variance in cost of human ETSP solutions. We investigated the role of conscientiousness, measured using Goldberg's Big-Five Inventory, and participant sense of direction, measured using the Santa Barbara Sense of Direction scale (SBSOD), on human ability to produce near optimal ETSP solutions. We showed, by combining the scores from the two tests into a single "impulsiveness vs cautiousness" dimension, that the new dimension is a significant predictor to the occurence of crossing-avoidance violations (a key metric of optimality).

Our findings suggest that people who scored lower in the component scores, i.e. those who are more impulsive, have a higher probability of producing graphs that contain crossings, and those who scored higher in the component scores, i.e., those who are more cautious, have a lower probability of producing graphs that contain crossings. Since graphs that contain crossings will always be suboptimal (Flood, 1956), our result suggests that both impulsiveness and cautiousness, which relate to both personality traits and cognitive analytic skills, impact human performance when undertaking the ETSP task.

Literature states that the perceived complexity of an ETSP is impacted by numerous variables, e.g. individual difference, the number of nodes, the geometric placement of nodes in the cartesian coordinate space, etc. Our findings support existing claims that individual differences significantly impact ETSP performance (Vickers et al., 2001; Vickers et al., 2004; Burns et al., 2006). Interestingly, unlike existing research, which primarily focuses on intelligence measures (e.g. Burns et al., 2006), we focused on formally considering the effect of impulsiveness on ETSP performance; the first study, to the best of our knowledge, to do so.

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Finally, no significant differences were identified in task performance as a result of an increase in the number of nodes in the graph (from 5 to 50 nodes), which contradicts the finding of previous results (Chronicle et al., 2008). We hypothesize that the reason we saw no difference, as a result of purely node number, is because graph complexity cannot be defined, especially at lower N values, by purely consider the number of nodes; since Euclidean complexity is impacted by a range of figural effects including: principles of good continuation (MacGregor et al., 2004); number of potential intersections in a graph (Vickers et al., 2003; Dry and Fontaine, 2014); cluster location and distribution, randomness, and regularity (Dry and Wagemans, 2012; MacGregor, 2015); and various properties of the convex hull (Kyritsis et al., 2017). The impact of figural effects, especially at lower N values, requires additional attention; if we are to more fully understand how node positioning in Euclidean space impacts occurrence of crossing-avoidance violations.

5. Conclusion

The results from our study aligns with the existing literature, i.e. that human performance when solving ETSP does not simply rely on low-level perceptual processes, but also higher-level cognitive abilities (Burns et al., 2006; Chronicle et al., 2008). Even though past literature has shown general intelligence to affect human ETSP tour costs, to the best of our knowledge this study is the first to provide evidence that self-reported measures, e.g., conscientiousness and sense of direction, have a causal relationship with human ETSP performance. Moreover, results suggest that conscientiousness and sense of direction are not just correlated, but also measure a third 'latent' variable, which we suggest to be a form of "impulsiveness".

It is important to note that the TSP is not just a theoretical problem. A wide range of new application areas can benefit from modern algorithmic approaches (Huang and Yu, 2017). Since humans are able to provide near optimal solutions to the ETSP, with near-linear efficiency, research to understand and model human problem solving heuristics can have considerable benefits in related application areas. Our study, however, suggests that the quality of human solutions can vary significantly. Accordingly, the development of a questionnaire that can help exclude participants who are likely to produce suboptimal solutions would be useful for this type of research; perhaps considering impulsiveness in combination with scores from general intelligence tests.

Finally, given the consequences of impulsive behavior, which can manifest as symptoms in various clinical conditions, we recommend further work, i.e., to consider whether reduced performance when solving optimization problems can be used as an objective indicator to highlight patients with symptoms of impulsivity.

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5.1. Limitations and future work

Our study did not allow for node revisiting, i.e., participants could not correct mistakes in their solutions during each trial. We believe that the inability to correct decisions, particularly in the early trials, could have been responsible for some initial increases in the amount of crossings in graphs. Even though graphs were randomly selected, and therefore increases should not result in any order effects, additional appreciation of this result would be good. It is worth noting that we did not measure reaction time (RT) during graph traversal; i.e., as participants moved from one node to the next. Even though we believe that conscientiousness, which is essentially a measure of planning behavior, will affect the overall time taken to solve the graph, additional research would be good to consider the relationship between individual factors and RT; as well the RT variability caused as a result of the number of potential intersections in a graph (see Vickers et al., 2003; Dry and Fontaine, 2014). Though it is clear that 'impulsiveness' has a part to play, we acknowledge that there are many possible confounding variables, which we did not control for in our study, that could account for some of the variance in our model; such as participant interest and participant intelligence. Accordingly, we cannot conclude that "impulsiveness", the dimension presented in this paper, is the best predictor of crossing-violations when discussing the effect of individual differences on human ETSP solutions. Finally, we did not investigate possible overlaps in variance between scores from other individual differences already shown to impact performance in the TSP such as Raven's performance (Vickers et al., 2004). We aim to address all these issues in future work.

Declarations

Author contribution statement

Markos Kyritsis: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

George Blathras: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Stephen Gulliver: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Vasiliki-Alexia Varela: Analyzed and interpreted the data; Wrote the paper.

Competing interest statement

The authors declare no conflict of interest.

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