Spatial exploration strategies in childhood; exploration behaviours are predictive of navigation success

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A B S T R A C T

Five- to 11-year-olds (N = 91) explored virtual environments with the goal of learning where everything was within the environment (1 trial; Experiment 1) or to find six stars (5 trials/condition; Experiment 2). Participants took part in a standard condition and in an overhead map condition in which they could view their location on a map. In Experiment 1, with increasing age, participants visited more of the environment, had longer path lengths and fewer pauses. In Experiment 2, navigation success (time per target collected) increased with repeated trials and was stronger in the overhead map condition. Associations between exploration behaviour and navigation success demonstrated that fewer pauses, visiting more areas of the environment and stronger target order consistency across trials, were associated with navigation success for both conditions. Additional input was also differentially observed for each condition; age and gender impacted performance in the overhead map condition, whilst the number of revisits impacted performance in the standard condition. Individual difference analysis (Latent Profile Analysis) of the standard condition revealed three profiles. These reflected cautious explorers who were poor at navigating (profile 2), active and efficient explorers who were good at navigating (profile 1) and active and less efficient explorers who were average at navigating (profile 3). This is a first step to understanding exploration behaviour in children and how this relates to navigation success.

Spatial navigation describes the skills required to know where you are in an environment and the ability to find places and to learn and retrace routes. These are essential skills to human development (Newcombe, 2019). It has recently been posited that navigation is one of three kinds of spatial skills which together constitute the spatial domain (Newcombe, 2018; Malanchini et al., 2020). Despite this new importance placed on navigation, we know almost nothing about spatial *exploration* as a mechanism to support navigational learning. Spatial exploration refers to the unconstrained exploration patterns exhibited during the encoding of spatial information, yet navigation is typically measured with reference to success in learning fixed routes, or by measuring spatial knowledge of an environment. We do know that children can explore large-scale space as soon as they can locomote, and that this is associated with changes in spatial cognition (Campos et al., 2000; Clearfield, 2004; Oudgenoeg-Paz, Leseman, & Volman, 2015). Thus, logic predicts that

exploration represents a basic building block for the development of spatial knowledge. A better understanding of exploration, and how it relates to navigation success will advance our theoretical understanding of navigation.

Here, we define spatial knowledge as the mental representation of the spatial layout of a known environment. In contrast, we define exploration with reference to variables which measure the behaviours and strategies used during the encoding of that spatial knowledge. The purest measures of exploration are in unknown environments where the individual has no spatial knowledge of that environment, but exploration behaviours also remain relevant while the individual is learning about the environment and refining their spatial knowledge.

Before discussing the literature on exploration, we outline the development of two types of spatial knowledge which we predict are supported by exploration. These are route knowledge and configural knowledge (Siegel & White, 1975). Route knowledge involves using landmarks (landmark knowledge; Siegel & White, 1975) as references to learn a fixed route. Even at two years, children can mentally represent space to determine whether to turn left or right to find their mother (Rieser, Doxsey, McCarrell, & Brooks, 1982; also see Hazen, Lockman, & Pick, 1978) and children as young as 6 years demonstrate route knowledge, i.e., they can learn a route from A to B (Bullens, Iglói, Berthoz, Postma, & Rondi-Reig, 2010). Route knowledge, however, is relatively limited because it is inflexible to deviations from the known route. Between 5 and 10 years, children develop knowledge of the spatial relations between places within an environment (Broadbent, Farran, & Tolmie, 2014; Bullens et al., 2010), with adultlike navigation observed from 12 years (Nazareth, Weisberg, Margulis, & Newcombe, 2018). This ability, known as configural knowledge or survey knowledge (Siegel & White, 1975), is a more efficient strategy because of its flexibility. Using configural knowledge people are able find shortcuts and alternative routes and to navigate to a known place when lost. Below, we discuss spatial exploration and how it might support the development of route knowledge and configural knowledge.

Jansen-Osmann and colleagues included an exploration phase in their studies with children and adults (Jansen-Osmann, Schmid, & Heil, 2007a; Jansen-Osmann, Schmid, & Heil, 2007b; Jansen-Osmann & Heil, 2007). Participants explored a virtual environment for 3 or 5 min. In Jansen-Osmann et al. (2007a), if the participant had not explored all paths within 5 min, they were given additional time. They report that 7- to 8-year-olds took more time to complete the exploration phase than adults. Interestingly, this was not coupled with longer distance travelled, which the authors suggest reflects more pausing in this age group during exploration. These studies did not, however, investigate how exploration relates to navigation success.

Cornell, Hadley, Sterling, Chan, and Boechler (2001) asked children to lead an experimenter to the furthest place they had been to without their parent, thus tapping into exploration opportunity. Twelve-year-olds walked farther than 6-year-olds, but the same distance as 8-year-olds. However, 8-year-olds took much less efficient routes than 12-year-olds when compared to the crow's flight line. With reference to spatial knowledge, this is indicative of stronger use of configural knowledge by the older group, and stronger reliance on route knowledge in the younger group. The use of landmarks also changed developmentally. When asked to name landmarks as they walked, 12-year-olds were more likely to name distant landmarks and to scan the horizon than 8-year-olds, which provides further indication of the development of configural knowledge of the environment. Whilst Cornell et al. (2001) did not measure exploration strategies per se, they did demonstrate that children's exploration experience of their own environment teaches them to learn to selectively attend to appropriate landmarks to find their way and that exploration is an important determinant of the development of spatial knowledge.

Vieites, Pruden, and Reeb-Sutherland (2020) measured participants' retrospective reporting of how far they were allowed to travel independently as children, alongside two concurrent navigation strategies. These were: route strategies (e.g., using landmarks and egocentric body movements, akin to route knowledge), and orientation strategies (e.g., using global references such as the sun, an aspect of configural knowledge). Vieites et al. (2020) reported that males travelled more as children, and used route strategies less as adults, compared to females. Mediation analysis demonstrated that travel as children partially mediated the sex difference in the use of route strategies in adulthood, but that route strategies remained negatively related to distance travelled after controlling for gender. This suggests that, akin to Cornell et al. (2001), reduced exploration opportunities in childhood are associated with the use of a route strategy over an orientation strategy. Note, however, that no relationship was observed between exploration opportunity and the use of orientation strategies (i.e., configural knowledge). This is not consistent with Cornell et al. (2001) and might be accounted for by the specific aspects of configural knowledge asked about by Vieites et al. (2020). In the current study, we address the gap in knowledge between exploration opportunity and navigation success by investigating the characteristics of exploration behaviours themselves, and how they relate to navigation success.

Vieites et al. (2020) hints at some gender effects in exploration. For traditional measures of navigational knowledge (e.g., correct turns during route recall, pointing in the direction of a target), a meta-analysis of 694 effect sizes across several navigation variables demonstrated a male advantage with small to medium effect sizes ($d = 0.34 - 0.38$) (Nazareth, Huang, Voyer, & Newcombe, 2019). Of note, gender effects increased with age such that studies with children (<13 years) revealed small effect sizes ($d = 0.15$) (Nazareth et al., 2019). Precisely why these gender differences exist is still a matter of discussion. Independent mobility in childhood is one potential contributor (Vieites et al., 2020). Newcombe (2020) also discusses home environment as a potential contributor (e.g., exposure to spatial language: Pruden & Levine, 2017; engagement in spatial play: Jirout & Newcombe, 2015). The study of exploration behaviours in childhood will help to determine whether individual differences in exploration contribute to the male advantage observed for some navigation variables.

In studies with adult participants, there has recently been direct focus on exploration strategies and how these relate to navigation success. Gagnon et al. (2018) used a desktop virtual environment to investigate exploration and its relationship to navigation success. Participants were asked to find three targets, without the aid of a map. They measured two exploration behaviours, revisiting previous locations and diffusion (the rate at which a participant visits unique locations). On finding each target, navigation error was assessed by asking participants to return to a home location and then to navigate back to the target. As a measure of configural knowledge,

pointing error was measured at the end of the study (pointing to the three target locations from home). Gagnon et al. (2018) report changes in exploration behaviours across trials evidenced by reduced revisiting and increased diffusion when locating target 3 compared to targets 1 and 2. Females also made more revisits and showed reduced diffusion relative to males. These differences partially accounted for gender differences in spatial knowledge, but over and above effects of gender, increased diffusion was related to reduced pointing errors, whilst reduced revisiting was related to reduced navigation error.

In a similar study, albeit with a map which indicated target locations, Munion, Stefanucci, Rovira, Squire, and Hendricks (2019) measured the ability of adult cadets to find five flags (targets) in a wooded area. Using GPS, Munion et al. (2019) determined that the ability to locate targets was associated with: travelling long distances before making a turn (directional persistence); pausing less; and making fewer revisits to locations that they had already been to. Furthermore, males located more flags, and this advantage was fully mediated by exploration strategy. That is, males showed more directional persistence, paused less, and made fewer revisits compared to females and these gender differences explained the gender differences in navigation success (finding the flags).

With the exception of Jansen-Osmann and colleagues, exploration strategies such as those measured by Munion et al. (2019) and Gagnon et al. (2018) have not been measured in childhood, and crucially there are no developmental studies of how exploration relates to navigation success. Given evidence for ontological differences in spatial knowledge in childhood (e.g., Bullens et al., 2010), and for direct relationships between exploration behaviours and navigation success in adulthood, it is likely that there are ontological differences in exploration behaviours in children, which support the development of spatial knowledge. Here, we characterise exploration in childhood and determine the developmental relationship between exploration behaviours and navigation success. This will provide important insight into *how* children gain spatial knowledge, i.e., the encoding processes that support spatial knowledge. We also investigate gender differences. Although gender differences in exploration behaviours in childhood are largely unknown, the small gender effects present in childhood in traditional studies of navigational knowledge (spatial knowledge and navigation success) suggest that small effects might be present for exploration.

Exploration behaviour was investigated in children aged 5–11 years using desktop virtual reality across two experiments. In Experiment 1, participants had three minutes to freely explore a virtual environment (similar to Jansen-Osmann et al., 2007b). This was designed to be akin to a real-life situation of visiting a town for the first time (a parallel for children might be a new softplay centre or playground). We were interested in whether exploration behaviours change with age. We hypothesised, based on research with adults (Gagnon et al., 2018; Munion et al., 2019), that with increasing age larger areas of the environment would be visited, the number of revisits to the same location would reduce and pausing would be less frequent. Jansen-Osmann and colleagues report no change in path length with age in their studies (Jansen-Osmann et al., 2007a, 2007b; Jansen-Osmann & Heil, 2007). However, because we were using a strict time limit, we predicted increased path length with increased age. We also anticipated that, if gender effects were present, this pattern would be more evident in males than females.

1. Experiment one: free exploration

1.1. Method

1.1.1. Participants

Children aged 5–11 years (N = 91; mean age: 9.26 years) were recruited through primary schools. N = 46 males (mean age: 9.53 years) and N = 45 females (mean age: 8.99 years) participated. Males and females did not differ in Chronological Age, t(89) = 1.57, p = .12. Ethical approval for Experiments 1 and 2 was obtained from the University ethics committee. Written consent was provided by parents/caregivers, verbal consent was given by participants.

Fig. 1. Example of a building block from the free exploration virtual environment used in Experiment 1.

1.1.2. Design and procedure

The virtual environment (VE) was created using Virtools 5.0 (Dassault Systems) and were presented on a 17-inch laptop. Participants moved around the virtual environment using the keyboard arrow keys (forward, right, left; horizontal plane).

Familiarisation trial: Participants were presented with a short empty corridor VE in which two changes in direction along right-angle turns were required to reach a target (a yellow star). The experimenter demonstrated how to move around the corridor VE using the keyboard controls. Once participants understood, it was their turn. Participants were told to navigate to a star and walk into it, which marked the end of the trial. Participants completed one familiarisation trial, or more if required (in practise this occurred infrequently), to ensure that they could move confidently and accurately in the VE.

Experimental trial: The experimental VE was constructed in a 300 × 300 virtual unit area bounded by four walls. The trial began at the 'home' location, which was the lower left corner of the VE and was coloured dark grey. Within the walls there were 10 building blocks (two 75×65units, two 60 ×45 units, and one each of 60 ×30 units, 75 ×75 units, 90 ×30 units, 30 ×75 units, 45 ×45 units, 45 ×60 units). A building block consisted of blocks of tall linked buildings (Fig. 1). A total of 40 proximal landmarks were included; four proximal landmarks surrounded each building block (one on each wall), two on corners and two that were along a wall, but not at a corner. A distant landmark appeared along three of the four perimeter walls in a triangular formation to aid orientation within the VE.

Participants were told that they had three minutes to learn as much as they could about where everything was in the VE. A blue bar on a white background was shown at the top of the screen that increased in length as the duration of the trial reduced.

Participant location was recorded as X and Y coordinates in whole units (the VE extended 300 ×300 units) every 200 ms. These were used to derive four variables, based on variables used in previous research (Gagnon et al., 2018; Jansen-Osmann et al., 2007a; Munion et al., 2019). First, the number of areas of the VE that were visited out of a maximum of nine. The nine areas were determined by dividing the VE into a 3 by 3 grid of 100 unit x 100 unit square areas. Second, the length of the path travelled by the participant in virtual units. Third, the number of times that a participant's path intersected with itself or the participant immediately retraced part of their path (i.e., they made a 180 degree turn and retraced their steps). These two kinds of behaviours were summed together and labelled as revisits. Fourth, the number of times that the participant paused during their 3-minute exploration of the VE. A pause was categorised as having no change in X and Y coordinates for 2 s or more (note, that we also measured the absolute length of pauses. Length of pauses was consistent across age, and thus our variable of number of pauses also reflects dwell time in the VE).

1.2. Results

The data were mostly not normally distributed (Kolmogorov-Smirnov, $p < .05$). Because the sample size was large enough for the central limit theorem to apply, parametric analyses were applied (Field, 2013).

Descriptive statistics for the 'number of areas visited' demonstrated that 43 (47%) participants visited all nine areas, and the distribution of the number of areas visited was skewed towards a high number of areas visited. This suggests that participants understood the brief, and that 3 min was sufficient to explore the whole VE.

To determine the relationship between chronological age and gender on each of the exploration variables, regression analyses were carried out. Predictor variables were entered in two steps with the enter method used for step 1 and a stepwise method for step 2. For step 1, chronological age and gender were entered, for step 2, the interaction term between chronological age and gender was entered. Because the stepwise method was used for step 2, the interaction term was only retained in the model if it was significant. There were four regression models, one for each of the exploration variables: path length; number of pauses; number of areas visited; number of revisits (Bonferroni corrected critical alpha: $p \leq .0125$). All variables were converted to z-scores prior to analyses. The collinearity statistics indicated appropriate Tolerance (all >0.02; Menard, 1995) and VIF scores (all <10; Myers, 1990). All four regression models

Table 1
Regression model of age and gender on each exploration behaviour.

Path length	β	t	p	F	Df	p	Adj. R²	Δ Adj.R²
				24.29	2, 88	< 0.001	.34	
Age (months)	.36	4.20	< 0.001					
Gender	-0.42	-4.79	< 0.001					
Number of pauses								
				20.52	2, 88	< 0.001	.30	
Age (months)	-0.29	-3.30	.001					
Gender	.44	4.88	< 0.001					
Number of revisits								
				10.00	2, 88	< 0.001	.17	
Age (months)	.19	2.00	.05					
Gender	-0.35	-3.63	< 0.001					
Number of areas visited								
Step 1				12.26	2, 88	< 0.001	.20	
Age (months)	.33	3.49	< 0.001					
Gender	-0.28	-2.89	.005					
Step 2				10.68	3, 87	< 0.001	.24	.04
Age (months)	.32	3.43	< 0.001					
Gender	-0.28	-2.99	.004					
Age (months)*Gender	.23	2.47	.015					

were significant, and the interaction terms was only retained in the model for number of areas visited. However, the p-value for this interaction term was below our critical alpha and is not explored further (Table 1).

As shown in Fig. 2, participants visited more areas, had longer path lengths and paused less frequently with increasing chronological age. As shown in Fig. 3, males had longer path lengths, visited more areas, paused less and made more revisits than females.

1.3. Discussion

For three of the four exploration variables, participant's exploration of the environment was strongly related to chronological age, with older children exploring a wider area of the VE, creating longer path lengths and pausing less than younger children. This suggests that this pattern reflects the optimal strategy for efficient free exploration. Males exhibited the same pattern as that shown for age, compared to females, which could suggest a male advantage for spatial exploration. The effect of path length appears to contrast with the lack of gender or age effects for this variable reported by Jansen-Osmann and colleagues. However, this simply reflects differences in task design with respect to the time limit, which was fixed in the current study, but flexible in the Jansen-Osmann studies. In contrast to the associations above, the pattern for the number of revisits within the environment is less age dependent, but differed by gender (males revisited more than females). This could reflect a more active strategy in males, which is not age dependent. It is important to note that effects of gender might be confounded by environmental factors. For example, we did not measure participants' experience with navigational computer games and thus we cannot determine whether the gender effects were influenced by experience with navigation games. Future research could seek to determine why gender differences exist. This could be investigated by asking participants about their home environment, daily range of activities, and navigation anxiety. Researchers would then be able to determine the impact of these factors on gender differences in spatial cognitive tasks, and to control for them.

Taken together, the patterns observed suggest that the optimal solution for freely exploring an unfamiliar environment is to cover as wide an area as possible, and to take minimal time to pause and think. This is consistent with adult data (Gagnon et al., 2018; Munion et al., 2019). The effect of pauses additionally suggests that with increasing age, participants took less time to stop and
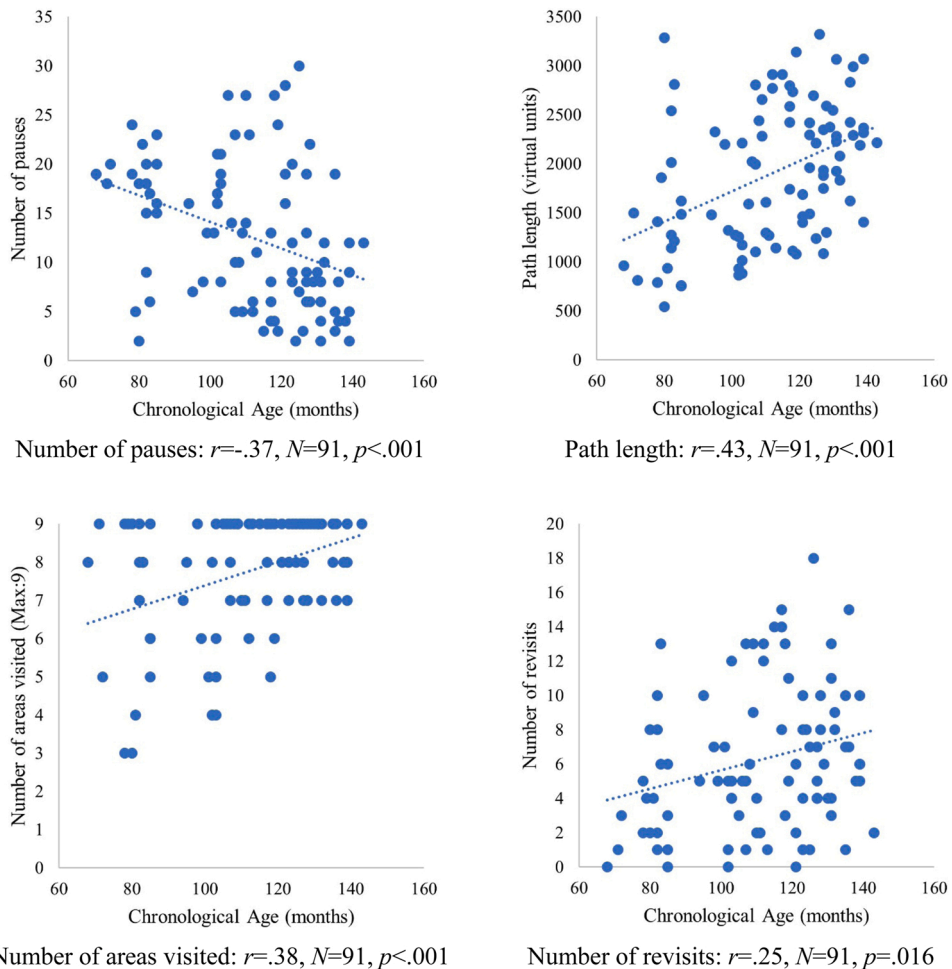

Number of pauses: $r=-.37$, $N=91$, $p<.001$

Path length: $r=.43$, $N=91$, $p<.001$

Number of areas visited: $r=.38$, $N=91$, $p<.001$

Number of revisits: $r=.25$, $N=91$, $p=.016$

Fig. 2. Correlations between Path length, Number of areas visited, Number of pauses and Number of revisits, with Chronological Age.
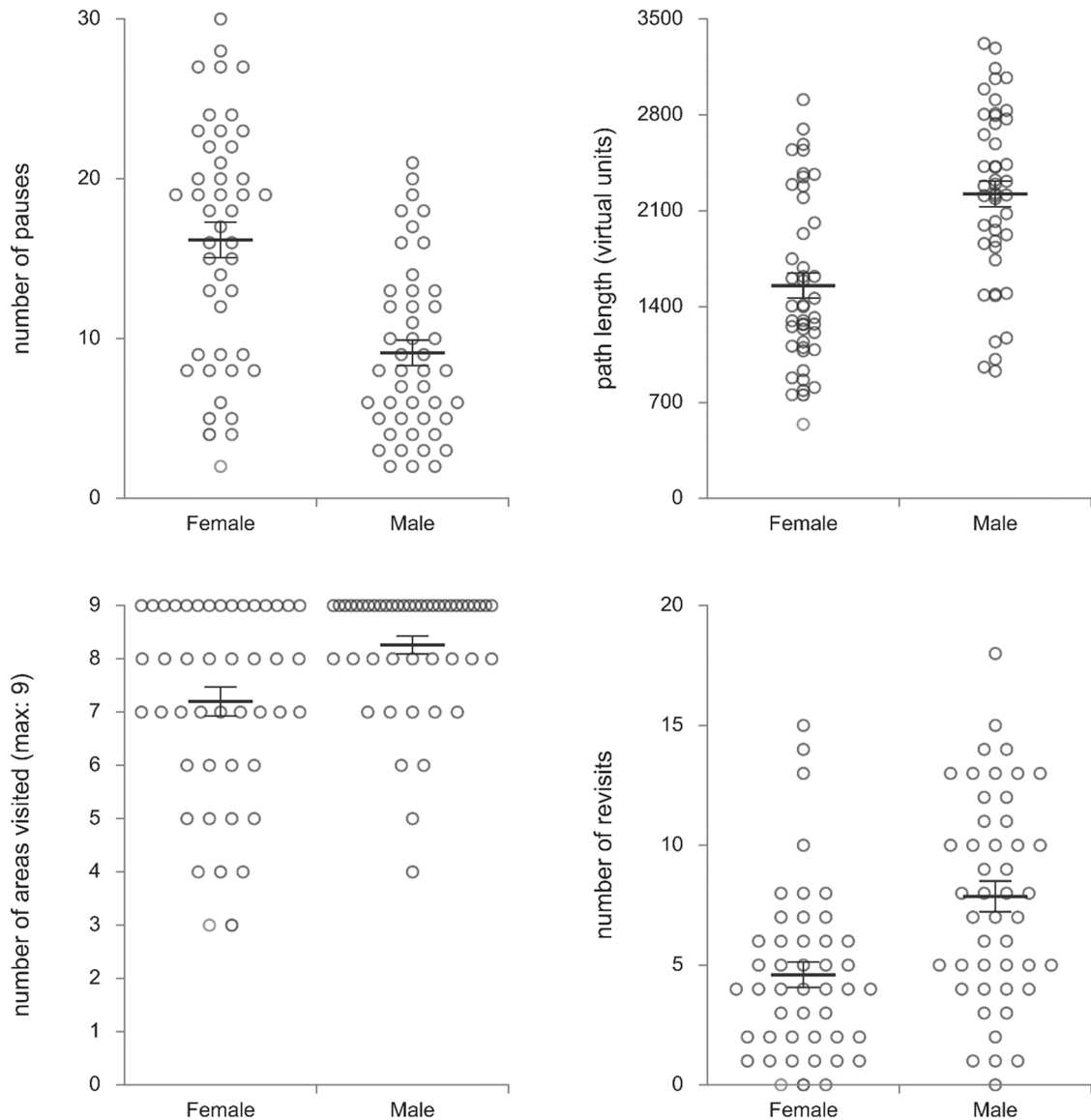
Fig. 3. Path length, Number of areas visited, Number of pauses and Number of revisits by gender.

strategize. Munion et al. (2019) refer to pauses as reflecting more cautious exploration behaviour, and thus a lower number of pauses reflects a strategy in which planning and decision making takes place online as people walk, i.e., an active strategy. The data also demonstrate gender differences, which appear to reflect a more active exploration strategy in males. While this led to more revisits, which could indicate less efficient exploration (Gagnon et al., 2018; Munion et al., 2019), in all other respects, this strategy appears to have given males an advantage over females. This gender difference is consistent with Nazareth et al.'s (2019) meta-analysis of navigation variables and suggests that exploration variables are subject to gender effects. However, as stated above, gender effects are interpreted tentatively due to the possibility of mediating environmental factors not measured here.

Although participants were instructed to learn where everything was in the VE, we did not measure learning and so do not know whether the patterns of exploration observed support associated spatial learning. Experiments 1 and 2 were designed to be complementary studies of free exploration (Experiment 1) and exploration with a goal (Experiment 2); this limitation is addressed in Experiment 2.

2. Experiment 2: exploration with a goal

In Experiment 2, we were interested in how exploration related to navigation success. Participants explored an environment with the goal of locating six stars (targets) and returning to 'home' within three minutes. Participants were given five trials in the same

environment (stars remained in the same locations across the five trials). Navigation success was measured as the time taken to collect the stars divided by the number of stars collected (time per star). We anticipated that by including a goal, exploration would become more strategic. Based on research with adults (Gagnon et al., 2018; Munion et al., 2019), we predicted navigational learning across the five trials as participants began to understand the environment. Developmentally, we predicted that older children would have stronger navigation success than younger children and that if gender effects were present, this would reflect stronger navigation success in males than females. We also hypothesised that higher navigation success would be supported by stronger consistency in the order of star collection between consecutive trials, indicative of spatial knowledge of the environment. With reference to exploration, we predicted that strong navigation success would be supported by shorter path lengths, visiting a larger expanse of the environment, revisiting the same location less frequently and making fewer pauses.

We were also interested in individual differences. Even in adulthood there are individual differences in the use of different types of spatial knowledge (referred to as navigation strategies) and some adults do not draw on configural knowledge (Weisberg & Newcombe, 2018) or change navigation strategies dependent on the complexity of the environment (Muryy & Glennerster, 2020). Weisberg and Newcombe (2016) report three types of navigation strategies in adults, imprecise navigators, non-integrators and integrators, the latter two categories reflecting the use of route knowledge and configural knowledge respectively. Nazareth et al. (2018) report the same three groups in childhood, and that in children these groups also reflect the age-related differences discussed earlier. Because of these known individual differences in navigation strategies, it makes sense that these might be supported by individual differences in exploration. This is investigated in the current study.

Whilst little is known about individual differences in exploration behaviours, Munion et al. (2019) refer to cautious vs. active exploration, and Cornell et al. (2001) refer to more efficient paths as reflective of the use of configural knowledge (also see Davies & Cashdan, 2019) and less efficient paths reflecting the use of route knowledge. Taken together, individual differences in the number of pauses might reflect an active vs. cautious strategy, and individual differences in path length might reflect the use of route knowledge or configural knowledge to determine the route to collect the six stars. It is not possible to predict how these two dimensions cut across one another.

As an additional factor, we were interested in whether participants' ability to see their location in real time on an overhead map would influence their performance. As such, participants took part in two conditions, a standard condition, and one in which they could view their real-time position on an overhead map in the corner of the screen. For a map to be useful, participants must be able to use the spatial relations between the features of the map and transform these to their viewpoint within the environment (Plester, Blades, & Spencer, 2006). Primary school children are able to understand that an aerial map is a representation of real space and are able to identify corresponding features of the real environment from an aerial photograph (Blades & Uttal, 1999, cited in Plester et al., 2006). There are developmental differences, however, in understanding the symbolic intent of maps (Myers & Liben, 2008) and interpreting scale from maps (Uttal, 1996; in Liben, 2009). Thus, we were confident that participants would be able to understand the representational nature of the overhead map, but the ability to use if usefully might be associated with age. We predicted stronger navigation success in the overhead map condition than in the standard condition, but that there would be a strong correlation between navigation success and age, particularly for the overhead map condition.

2.1. Method

2.1.1. Participants

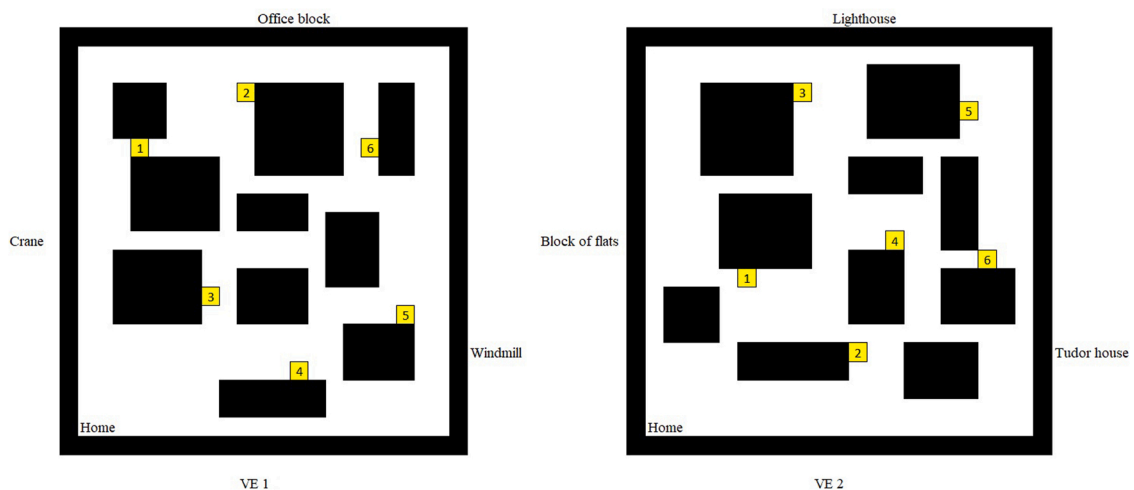The same participants as Experiment 1 took part in Experiment 2.

Fig. 4. Layout of VE 1 and VE2 used in Experiment 2. Numbers indicate locations of targets (stars).

2.1.2. Design and procedure

Experiment 2 was conducted immediately after Experiment 1, in the same session (up to forty minutes, with breaks). Participants attempted to locate six targets (stars) within a VE with and without the presence of an overhead, 'satellite navigation'-style view map of the environment, with five trials per condition. Two VEs were created which were counterbalanced across overhead map and standard conditions.

VE 1 and VE 2 contained ten buildings, three distant landmarks and 40 proximal landmarks within a 300 × 300 unit environment bounded by four walls (as in Experiment 1). Different landmarks were used in VE1 and VE2, and these differed from those used in Experiment 1.

There were six stars in each condition and at least one (and a maximum of two) appeared in each quadrant of the VE for VE 1 and VE 2 (Fig. 4). Each star was placed next to a proximal landmark. To ensure that participants recognised that they were in different VEs between conditions the perimeter walls of the VEs were uniquely coloured; for VE 1 the walls were red, for VE 2 the walls were blue.

Participants were told that they were on a treasure hunt to find six stars and bring them back to 'home' within three minutes (time remaining indicated by the blue bar at the top of the screen). When they collected a star it disappeared from within the VE and a congratulatory sound was played. The number of stars collected was shown in a score board on the left side of the screen, the stars were shown as grey on the score board when they were yet to be collected and yellow once collected (Fig. 5). Equal numbers of participants were assigned VE 1 or VE 2 for the standard condition, with the remaining VE being used for the overhead map condition. The standard (without map; five trials, three minutes each) condition was always presented first to avoid carryover effects of strategies learnt using the presence of the map. For the overhead map condition (five trials, three minutes each), participants were told that this time there would be a map on the screen that might help them (see Fig. 5). The map appeared at the bottom right and depicted: the outline of the buildings present in the environment (as white blocks); the participant's current location (as a blue dot which moved in real-time contingent with the participant's location); the 'home' location (a dark grey square); the three distant landmarks for the VE (it did not display proximal landmarks); and the stars that had been collected (stars were not visible on the map prior to being collected). For both conditions participants started each trial at 'home' and then attempted to find each star before returning to 'home' within a three minute time limit. The trial ended at three minutes regardless of this goal being achieved. Participants completed five trials per condition. Star locations were identical across the five trials of each condition.

Dependent variables for each trial were recorded with respect to spatial knowledge and to exploration patterns. Exploration variables were as in Experiment 1 (note, that we also measured the absolute length of pauses. Consistent with the variable 'number of pauses', 'length of pauses' also reduced with age, and thus our variable of number of pauses also reflects dwell time in the VE). The first spatial knowledge variable was the number of stars collected divided by the time that each participant spent in the VE, a 'time per target' variable. Time in the VE either timed out at 180 s (if the participant was still looking for stars and/or had not returned to the home location) or stopped at the point at which the participant had collected all 6 stars and returned to the home location. The second spatial knowledge variable captured participant's route creation across the five trials. This was a measure of consistency in the order of star collection over consecutive trials, and thus a measure the extent to which star collection became systematic as the participant learnt their way around the environment. The following formula was used: Sum of differences x [(6-sequence length)/6]. The first part of the formula was calculated by representing each star as a number, and documenting the star order collection for each trial (e.g. Trial 1 star order collection: 2, 3, 5, 1, 4, 6; Trial 2 star order collection: 3, 5, 1, 6, 4, 2; Trial 3…, etc.), and subtracting these values between consecutive trials. If a star was not collected, the subtraction was replaced with a value of 6. The absolute values of these six differences were then summed such that a value close to zero represents a more consistent order (e.g. For the example trials above, the absolute subtracted values would be: 1, 2, 4, 5, 0, 4; and the sum would be: 16). The second part of the formula captures common sequences that are shifted in the overall order of star collection from one trial to the next. In the examples above, both Trials 1 and 2 share a sequence

Fig. 5. A screenshot from the overhead map condition showing the target counter and map.

of '3, 5, 1', but the sequence falls in a shifted position for each trial. This common sequence is not captured by simple subtraction. Thus, for shared sequences of 3 or more stars (between two consecutive trials) we credited this be multiplying scores by the proportion of the sequence that was not shared across two consecutive trials, i.e. (6-sequence length)/6. For the example trials above, this would by 16 x $(6-3)/6 = 8$. Thus, the lower the target consistency score, the higher the consistency in target order between trials.

2.2. Results

One child did not complete the 5th trial of the overhead map condition and three children only completed one trial of the standard condition. This analysis therefore included 87 children.

2.2.1. Analysis strategy

The time per target variable and all exploration variables were not normally distributed (Kolmogorov-Smirnov, $p < .05$). Target order consistency scores data were broadly normal (Kolmogorov-Smirnov, $p > .05$ for the majority of variables). Because ANOVA is robust to violations of assumptions of normality, parametric analyses were applied (Blanca et al., 2017). Further, because the sample size was large enough for the central limit theorem to apply, parametric analyses were used (Field, 2013).

2.2.2. Navigation success

Before investigating how exploration behaviours support navigation success, it is important to determine whether participants gained spatial knowledge across the five trials, and whether this was impacted by the presence of an overhead map. ANOVA of the measure of navigation success (time per target) was carried out with Trial number (5 levels) and Condition (overhead map, standard) as within participant variables (Fig. 6). The main effect of trial indicated learning with repeated exposure to the environment; there was a linear decrease in time per target across trials, reported as a linear contrast, $F(1, 86) = 88.94, p < .001, \eta_p^2 = .51$. There was also a main effect of Condition, $F(1, 86) = 8.55, p = .004, \eta_p^2 = .09$ due to stronger performance in the overhead map condition than the standard condition. The interaction between Trial and Condition was not significant ($F<1$).

2.2.3. Associations between exploration and navigation success

Having established that participants had gained spatial knowledge of the environment, associational analyses were carried out to ascertain the associations between exploration and target consistency score, with navigation success. A mean time per target variable was created for each condition (mean time per target across the five trials). Bivariate correlation matrices are presented below, per condition (Tables 2 and 3). Each matrix includes the four exploration variables and star order consistency (summed across trials), and mean time per target. To correct for multiple comparisons, a critical alpha of $p \leq .001$ was used, with significance marked with a * .

Regression analyses were carried out to determine the predictive value of the exploration and target consistency variables on navigation success (i.e., mean time per star). Two hierarchical regression analyses were carried out with time per target as the outcome variable, one per condition (overhead map condition, standard condition). For each regression analysis, the contribution of five predictors, i.e., the four exploration variables (path length, revisits, number of areas visited and number of pauses) and the measure of target consistency, on navigation success, was investigated. Each model also took into account the effects of age and gender. All variables were converted to z-scores prior to analyses. Effects of age in months and gender were entered in step 1 as control variables. The predictor variables were entered in step 2. The collinearity statistics indicated appropriate Tolerance (all >0.02; Menard, 1995) and VIF scores (all <10; Myers, 1990).

Standard condition (Table 4): The model accounted for 79.6% of the variance in navigation success. In step 1, the control variables, age and gender accounted for 39.2% of variance. The experimental variables, added as step 2, accounted for an additional 40.4% of variance. In the final model, number of pauses, number of areas, number of revisits and target consistency scores were all unique predictors to the model (path length, age and gender were not).

Overhead map condition (Table 5): The model accounted for 81.7% of the variance in navigation success. Age and gender (step 1)
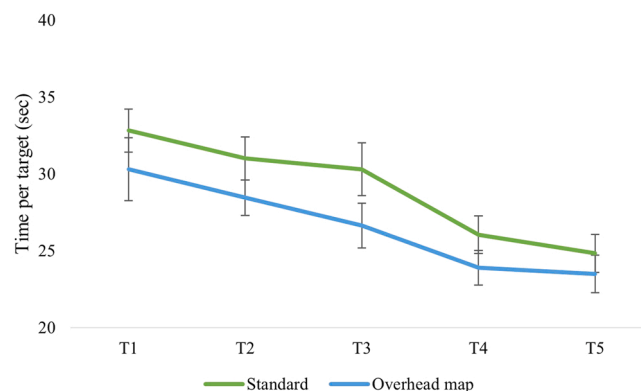

Fig. 6. Time per target collected as a function of learning across trials, displayed per condition.

Table 2

Standard condition, correlation between measures.

	2	3	4	5	6	7
1. Time per target	-.54*	.77*	-0.33*	-0.55*	-0.09	.78*
2. Age (months)	/	-.49*	.11	.28	-0.04	-0.53*
3. Pauses		/	-.63*	-0.43*	-0.46*	.62*
4. Path length			/	.50*	.70*	-0.20
5. Areas				/	.20	-0.40*
6. Revisits					/	-.10
7. Target consistency						/

Table 3

Overhead map condition, correlations between measures.

	2	3	4	5	6	7
1. Time per target	-.60*	.70*	-0.09	-0.47*	.12	.81*
2. Age (months)	/	-.45*	-0.10	.22	-0.20	-0.44*
3. Pauses		/	-.50*	-0.45*	-0.31	.52*
4. Path length			/	.40*	.83*	-0.01
5. Areas				/	.22	-0.33*
6. Revisits					/	.11
7. Target consistency						/

accounted for 49.2% of variance. The experimental variables (step 2) accounted for an additional 32.5% of variance. In the final model, age, gender, number of pauses, number of areas and target consistency scores were all unique predictors to the model (path length and number of revisits were not). To summarise, for both the standard and overhead map conditions, number of pauses, number of areas and target consistency scores were significant predictors of navigation success. In the standard conditions, number of revisits was also significant, whilst in the overhead map condition, age and gender were also significant.

The final regressions were designed to determine how exploration in an unfamiliar environment relates to later navigation success. In the first of these regressions (Table 6) data from Experiment 1 was used to determine whether the characteristics of free exploration, measured in Experiment 1, predicted navigation success (Experiment 2 time per target). Predictor variables were the four exploration variables from Experiment 1. In the second of these regressions (Table 7) data from Trial 1 of Experiment 2 (when participants had an exploration goal, but no knowledge of the environment) was used to predict overall navigation success in the same Experiment. Predictor variables were the four exploration variables from Trial 1 of Experiment 2. Mean time per target collected in the standard condition of Experiment 2 was used as the outcome variable. Age and gender were entered in step 1 and the four predictor variables (path length, revisits, number of areas visited, number of pauses) entered in step 2. The collinearity statistics indicated appropriate Tolerance (all >0.02; Menard, 1995) and VIF scores (all <10; Myers, 1990).

The regression model of Experiment 1 performance on Experiment 2 navigation success accounted for 51.2% of the variance in navigation success (Table 6). In step 1, the control variables, age and gender accounted for 39.2% of variance. The experimental variables, added as step 2, accounted for an additional 12.0% of variance. In the final model, only age was a unique predictor of the model, which suggests that the different goals of Experiments 1 and 2 elicited different exploration strategies.

The regression model of Experiment 2 Trial 1 performance on Experiment 2 navigation success accounted for 69.8% of the variance in navigation success (Table 7). In step 1, as above, the control variables, age and gender accounted for 39.2% of variance. The experimental variables, added as step 2, accounted for an additional 21.2% of variance. In the final model, age, number of areas and number of pauses were unique predictors of the model, which suggests that when asked to explore with a goal, behaviour in an

Table 4

Regression model of variables predicting navigation success (time per star) in the standard condition.

Standard condition	β	t	p	F	Df	p	Adj. R^2	Δ Adj.R^2
Step 1				28.76	2, 84	< 0.001	.39	
Age (months)	-0.49	-0.5.69	< 0.001					
Gender	.34	3.95	< 0.001					
Step 2				48.81	7, 79	< 0.001	.80	.41
Age (months)	-0.01	-0.14	.891					
Gender	.01	.191	.849					
Number of pauses	.57	6.10	< 0.001					
Path length	.09	1.00	.32					
Number of areas	-0.24	-0.388	< 0.001					
Number of revisits	.19	2.61	.01					
Target consistency	.36	5.01	< 0.001					

Table 5
Regression model of variables predicting navigation success (time per star) in the overhead map condition.

Overhead map condition	β	t	p	F	Df	P	Adj. R^2	Δ Adj.R^2
Step 1				42.65	2, 84	< 0.001	.49	
Age (months)	-0.54	-6.77	< 0.001					
Gender	.39	5.02	< 0.001					
Step 2				56.02	7, 79	< 0.001	.82	.33
Age (months)	-0.17	-2.89	.005					
Gender	.12	2.09	.04					
Number of pauses	.30	3.69	< 0.001					
Path length	-0.004	-0.04	.97					
Number of areas	-0.16	-2.81	.01					
Number of revisits	.17	1.87	.07					
Target consistency	.47	7.87	< 0.001					

Table 6
Regression model of Experiment 1 variables predicting navigation success (time per star) in the Experiment 2 standard condition.

Standard condition	β	t	p	F	Df	p	Adj. R^2	Δ Adj.R^2
Step 1				28.76	2, 84	< 0.001	.39	
Age (months)	-0.49	-0.5.69	< 0.001					
Gender	.34	3.95	< 0.001					
Step 2								
Age (months)	-0.31	-3.67	< 0.001	7.83	6, 86	< 0.001	.51	.12
Gender	.14	1.53	.13					
Number of pauses	-0.04	-0.09	.93					
Path length	-0.37	-1.80	.08					
Number of areas	-0.09	-0.76	.45					
Number of revisits	-0.07	-0.60	.55					

Table 7
Regression model of Time 1 Experiment 2 variables predicting navigation success (time per star) in the Experiment 2 standard condition.

Standard condition	β	t	p	F	Df	p	Adj. R^2	Δ Adj.R^2
Step 1				28.76	2, 84	< 0.001	.39	
Age (months)	-0.49	-5.69	< 0.001					
Gender	.34	3.95	< 0.001					
Step 2								
Age (months)	-0.23	-2.94	.004	22.85	6, 86	< 0.001	.60	.21
Gender	.054	.65	.52					
Number of pauses	.47	4.08	< 0.001					
Path length	-0.041	-0.31	.76					
Number of areas	-0.26	-3.27	.002					
Number of revisits	.084	.76	.45					

unfamiliar environment predicts later navigation success (i.e., once the environment is familiar). The significance of number of areas and number of pauses as predictors is also consistent with the regression models above (for both standard and overhead map conditions). This consistency across the regression models highlights the consistent importance of these two exploration variables for navigation success from the outset, when the environment is unfamiliar as well as when learning the environment.

2.2.4. Individual differences

Latent Profile Analysis (LPA) is an exploratory data-driven approach to understanding heterogeneity in a sample. LPA organises the sample into profile subgroups. Each profile represents a homogenous subset of the sample, who are characterised by the same pattern

Table 8
Model fit statistics for latent profile analysis models.

Model	BIC	SABIC	Entropy	BLRT p-value	N assigned to each Profile (P)
1-profile	5028.277	4990.413	1	NA	P1 = 87
2-profile	4820.054	4760.103	0.974285	0.009901	P1 = 59, P2 = 28
3-profile	4788.792	4706.753	0.914789	0.009901	P1 = 20, P1 = 28, P3 = 39
4-profile	4746.263	4642.138	0.938793	0.009901	P1 = 20, P2 = 10, P3 = 38, P4 = 19
5-profile	4742.101	4615.888	0.930685	0.009901	P1 = 6, P2 = 10, P3 = 23, P4 = 19, P5 = 29
6-profile	4765.259	4616.959	0.891761	0.633663	P1 = 24, P2 = 10, P3 = 14, P4 = 19, P5 = 14, P6 = 6

of responses on the chosen set of variables (Berlin, Williams, & Parra, 2014). Here, we are using it to determine latent profiles of our set of exploration and spatial knowledge variables.

The four exploration variables, target consistency score and time per target variables were entered into the LPA. LPA was conducted using R version 4.0.3 with R studio version 1.3. Taking an exploratory approach, models with up to six latent profiles were fit to the data (Table 8). The model with the optimal number of profiles was determined using the following criteria: low Bayesian Information Criterion (BIC) and sample-adjusted BIC (SABIC), indicative of better model fit; significant Bootstrap Likelihood Ratio Test (BLRT); high entropy values (see Berlin et al., 2014).

Model fit: Observing BIC values in Table 8, the lowest BIC and SABIC values are for model 5, and these values increase from model 5 to model 6, suggesting that model 5 has the least unexplained variance. With reference to BLRT, a significant p-value indicates a significant difference between k profiles and k-1 profiles. LPA solutions were significant for models 1–5 (p = .01), but non-significant for model 6, thus indicating that model 6 is not an improvement on model 5. Entropy varies from zero to one. The closer entropy is to one, the fewer classification errors. Entropy for all models was above 0.9 for models 1–5, but not model 6. Consideration of the smallest profile was also considered. The smallest profile for model 5 was N = 6, whilst the smallest profile for the model 4 was N = 10, which were not deemed reliable (Lubke & Neale, 2006). The smallest profile for model 3 was N = 20. Taken together, the 3 profile model was accepted.

Table 9 details the means and standard deviations for the six variables for each of the 3 profiles. The standardised means for each measure are plotted per profile in Fig. 7. Observation of Fig. 7 demonstrates that for each profile, target consistency is aligned with navigation success. The negative z-scores for both navigation success and target consistency demonstrate that profile 1 included participants with relatively strong navigation (i.e., the lowest scores on these measures). In addition to strong navigation success and target consistency, participants in this profile were characterised as making few pauses, short path lengths and few revisits. Profile 2 included participants with relatively weak navigation and target consistency (i.e., high z-scores on these variables). Whilst this profile also had short path lengths and few revisits, it differs from the other profiles due to long pauses and a wide range in the number of areas visited. Profile 3 represented participants with broadly average navigation and target consistency, and low numbers of pauses. It differs from the other profiles due to long path lengths and high numbers of revisits. Thus, it appears that profile 2 represents participants with a cautious approach to exploration who pause a lot thus also limiting their path length, and develop limited spatial knowledge of the environment. Profiles 1 and 3 are both active strategists (i.e., few pauses), but profile 1 participants take more efficient paths (short path lengths and few revisits; perhaps indicative of the development of configural knowledge), than profile 3 (perhaps indicative of the development of route knowledge).

Investigation of the age and gender of each profile demonstrated significant differences in age across the three profiles, $F(2, 84)=$ 15.47, $p < .001$, $\eta_p^2 = .27$. Tukey pairwise comparisons revealed significant differences between all pairs (profile 2 < profile 3 < profile 1; $p < .05$). There was also a significant association between profile and gender, $\chi^2(2)= 26.61, p < .001$. Adjusted standardised residuals indicated that this was driven by an association between profiles 1 and 3 with males (adjusted residual profile 1 = −2.5; adjusted residual profile 3 = −2.7) and an association between profile 2 and females (adjusted residual profile 2 =5.1).

3. General discussion

3.1. Navigation success

In Experiment 2, participants could find the targets and return home within three minutes. With respect to within-participant analyses of time per target (hereafter referred to as 'navigation success'), participants demonstrated linear improvement in navigation success across the five trials. This is indicative of learning, i.e., that participants had gained spatial knowledge of the environment. Navigation success was stronger in the overhead map condition than the standard condition. This suggests that children were able to integrate the map representation with the first-person view, to navigate (Plester et al., 2006).

3.2. Predictors of navigation success

For Experiment 2, over and above associations with age and gender, the full model accounted for a further 41% (standard condition) and 33% (overhead map condition) of variance in navigation success. Standardised Betas demonstrated that target consistency was a strong predictor of navigation success. This was expected and indicates that spatial knowledge of the environment (route knowledge or configural knowledge) is important for navigation success.

The association between exploration performance and navigation success is consistent with studies that have investigated this association in adults (Gagnon et al., 2018; Munion et al., 2019) and supports Cornell et al.'s (2001) developmental findings. Number of areas visited and number of pauses was a significant predictor for both conditions. Number of areas is consistent with Gagnon et al.'s (2018) diffusion variable, who demonstrated that diffusion was a significant predictor of configural knowledge (pointing error). If the same is true for children, then visiting a larger number of areas during exploration could contribute to the development of configural knowledge. This variable also aligns with Roaming Entropy (i.e., variability in physical location over a given time), which Heller, Shi, and Ezie (2020) associate with the neural reward systems related to environmental novelty (Heller et al., 2020 did not measure navigation success), thus also implicating a reward value of visiting more areas. An association between fewer pauses and higher navigation success is consistent with Munion et al.'s (2019) adult data. As discussed in relation to Experiment 1, and supported by our Latent Profile Analysis, this suggests that an active exploration strategy is effective for navigation success. The patterns of exploration which support the development of route knowledge vs. configural knowledge are discussed further below with reference to individual

Table 9

LPA Profile characteristics: mean (SD).

	Profile 1	Profile 2	Profile 3
Descriptive statistics			
N	20	28	39
M:F	15:5	3:25	26:13
CA	124.4(13.57)	97.21(18.86)	112.41(17.15)
LPA variables			
Time per target	19.49(7.24)	39.05(8.85)	26.38(4.50)
Target consistency	30.38(10.74)	62.36(20.31)	42.19(13.90)
Pauses	11.15(7.36)	99.25(23.41)	19.54(12.63)
Path length	8383.01(1293.93)	7408.80(1042.48)	11,272.90(925.36)
Areas	42.40(2.50)	41.21(2.78)	43.79(1.28)
Revisits	19.30(8.74)	16.61(7.17)	35.82(11.06)
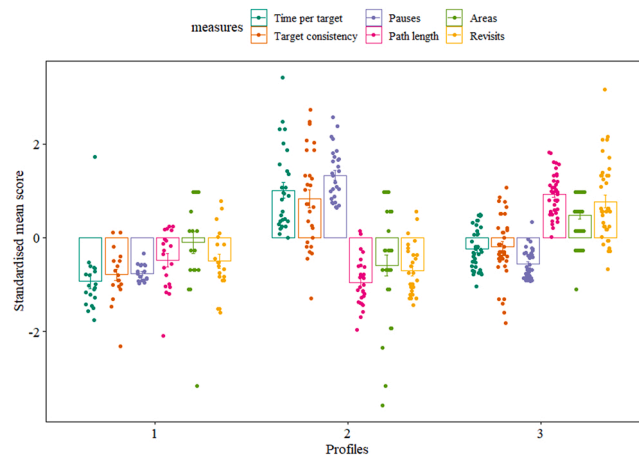
Fig. 7. Latent Profile plot of Z scores (means; standard error) for each measure.

differences.

For the overhead map condition, but not for the standard condition, age and gender remained significant predictors when the exploration variables and star order consistency variables were entered into the model. This suggests that the use of an overhead map is developmentally sensitive and gender sensitive in a way that the standard condition is not. This is consistent with the literature on map use. With respect to gender, Liben, Myers, Christensen, and Bower (2013) report poorer map use performance in 9- to 10-year-old girls than boys, possibly due to spatial skills being a better predictor of map use for boys than girls. Note, also, that these differences could also reflect the influence of environmental factors such as computer gaming, as discussed in Experiment 1. With respect to age, this likely signifies age limitations in using the map. For example, difficulties in understanding symbolic meaning from maps (Myers & Liben, 2008) and interpreting scale (Uttal, 1996; in Liben, 2009). Other map-related factors not measured here might also have contributed to performance (e.g., spatial scaling, attentional switching, working memory).

Returning to the standard condition, path length was not a significant contributor. This likely reflects, as seen in the Latent Profile Analysis, that path lengths can be short due to participants being very cautious and failing to collect all targets and can also be short from participants being very efficient in collecting all targets quickly, thus disrupting any linear relationship with navigation success. Number of revisits was a significant predictor for the standard condition, but not for the overhead map condition. As stated above, the difference between conditions likely stems from the input from age and gender in completing the overhead map condition, over and above these exploration variables. For the standard condition, fewer revisits were related to better navigation success, and thus reflect a more active strategy. We return to this later when discussing individual differences.

We were also interested in the predictive power of a single experience of exploring an unfamiliar environment on navigation success, i.e., when participants had no spatial knowledge of the environment. This is important to determine, because arguably for the analyses above, once the environment begins to become familiar, the contributions of exploration behaviours vs. participant's representation of the spatial layout, to navigation success cannot be disentangled. A single experience in an unfamiliar environment does not have this confound. Exploration in Experiment 1 accounted for an additional 12% of variance in navigation success in Experiment 2. However, whilst age remained a significant predictor, none of the exploration variables significantly predicted navigation success. This likely reflects the different goals of Experiment 1 and Experiment 2, in which the former was simply about exploring the whole environment and the latter involved exploring with a goal (referred to as "undirected wayfinding and "directed wayfinding, uniformed search" respectively in Wiener, Büchner, and Hölscher (2009) wayfinding taxonomy). In contrast, exploration in trial 1 (when the

environment was unfamiliar) of Experiment 2 accounted for an additional 21% of variance in navigation success in Experiment 2 over and above age and gender alone. Specifically, significant contributions were observed for age, number of pauses and number of areas visited. This is an important finding because it demonstrates that behaviour in a three-minute goal-directed exploration task in an unfamiliar environment is associated with navigation success. That is, fewer pauses and covering more areas of the environment are a good initial strategy for future navigation success and is a pattern consistent with developmental maturation. Observation of the standardised Betas for all regression models from Experiment 2 demonstrate a consistent and strong input from the number of pauses and the number of areas. This suggests that these exploration variables are crucial for navigation success both when the environment is unfamiliar (when no spatial knowledge has been gained), and during the learning of the environment (when spatial knowledge is being attained). This finding is also consistent with the association between exploration and navigation success in adults (Gagnon et al., 2018).

Individual differences analysis of the standard condition identified three patterns of exploration. Profile 1 had the oldest mean age, was associated with males and had strong navigation success and strong target consistency, indicative of a good spatial knowledge of the environment. This was supported by an exploration strategy of relatively low numbers of pauses and revisits and short path lengths. The low number of pauses suggests an active strategy and the short path lengths coupled with high navigation success suggests the use of configural knowledge (Cornell et al., 2001). Profile 2 included the youngest children and was associated with females. These children had the weakest navigation success and low target consistency, suggestive of limited spatial knowledge of the environment. The short path lengths and low number of revisits in this profile were coupled with high number of pauses and high variation in the number of areas visited. This suggests that the short path lengths were due to participants running out of time, rather than efficiency of travel. Children in profile 3 were average. That is, they were the middle age group of the three profiles and displayed average navigation and target consistency. Similar to profile 1, however, this profile was associated with males and exhibited relatively low numbers of pauses. Profile 3 differs from the other profiles due to long path lengths and high numbers of revisits. Thus, children in this profile and children in profile 1 appear to be both using active strategies, but profile 3 children take less efficient paths, perhaps indicative of the use of route knowledge (Cornell et al., 2001). The impact of pauses across these profiles is reminiscent of the rodent literature, in which exploratory pauses and Vicarious Trial and Error (VTE) have been reported for unknown and known environments respectively (Redish, 2016). Exploratory pauses reflect the encoding of a new environment, whereas VTE reflects deliberation at choice points as the rat consults their spatial knowledge. VTE reduces with experience of an environment as navigating becomes more automated (Redish, 2016). Taking this into account, an active strategy (profiles 1 and 3) might reflect more efficient encoding of the environment (i.e., the development of spatial knowledge of the environment), enabling faster automation across the five trials. In contrast, a cautious strategy (profile 2) might reflect less efficient encoding and/or slower automation and thus more need for deliberation.

Whilst we have theorised that active and cautious exploration strategies support the development of configural knowledge or route knowledge respectively, it is important to consider the possibility of a bidirectional relationship between exploration strategy and spatial knowledge. That is, we also posit that, during the learning of an environment, spatial knowledge is constructed which can be consulted to guide exploration. For example, exploration which draws on configural knowledge can enable individuals to find short-cuts. Clearly, our data demonstrates that exploration strategies are applied in novel environments before any spatial knowledge is available, and that the same strategies are applied as the environment becomes familiar, but this does not rule out the possibility of some bi-directional influence once the individual starts to form a spatial representation of the environment.

The current study, consistent with studies with adults (Gagnon et al., 2018; Munion et al., 2019), demonstrates how vital exploration strategies are for navigation success. Yet, paradoxically we know very little about exploration. Recent models of spatial cognition place navigation as a central subdomain (Newcombe, 2018; Malanchini et al., 2020). It is important that we better understand the exploration mechanisms which support the development of spatial knowledge, and how these develop. Furthermore, considering evidence that contemporary children are given less independence to explore compared to the generations before them (Shaw et al., 2015) it is possible that lack of independent exploration negatively impacts the development of navigation skills. There is now plentiful evidence that spatial competence in childhood is positively associated with success in Science, Technology, Engineering and Mathematics (STEM) subjects (e.g., Gilligan, Flouri, & Farran, 2017; Uttal et al., 2013). Whilst navigation is yet to feature in studies designed to determine the influence of spatial competence on STEM skills, it is highly likely that the skills required to successfully navigate (including exploration abilities) comprise the set of 'spatial thinking' skills that are important for STEM expertise (Newcombe, 2018). Indeed, Shaw et al. (2015) report positive correlations between Childhood Independent Mobility and PISA (Programme for International Student Assessment) educational attainment scores, which gives some indication of the importance of exploration. Given the ease at which exploration experience can be provided to children both digitally and in the real world in a safe manner, it could be a useful tool to improve navigation skills, with positive downstream impact on STEM competence.

The current study used desktop virtual reality, and whilst there is evidence that virtual navigation taps into the same mechanisms as real-world navigation (Coutrot et al., 2019), future research could investigate exploration variables in children in the real world. Navigation success measures and spatial knowledge measures often draw on executive function and long-term memory (e.g., Purser et al., 2012). Our study does not determine the relative contributions of exploration behaviours vs. executive functions and long-term memory on spatial knowledge. In future research it would be important to determine these contributions within the same model. Our study also did not determine the source of gender differences. Future research could determine whether the small gender effects observed here are explained by environmental factors such as experience with navigation games and navigation anxiety. A strong developmental advantage of exploration measures, in contrast to spatial knowledge measures, is that they are relatively pure and developmentally sensitive spatial measures which require minimal instruction. Whilst we used desktop virtual reality, which restricts the age range that the tasks can be used with, future research could investigate the utility of measuring exploration from infancy to old

age using GPS tracking.

This is one of the first studies to investigate exploration behaviours in children and its association with navigation success. Our findings highlight the importance of exploration behaviours as a vehicle to understand the development of spatial knowledge, and that the optimal exploration strategy is to pause less, visit more areas of the environment, make fewer revisits and to have shorter path lengths. This pattern, we propose, is more strongly associated with the development of configural knowledge. In contrast, a similar active strategy, but with less efficient, longer paths, might reflect the use of route knowledge.

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CRediT authorship contribution statement

Emily Farran: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Supervision, Visualization, Writing – original draft. **Mark Blades**: Conceptualization, Funding acquisition, Methodology, Writing – review & editing. **Kerry D. Hudson**: Conceptualization, Investigation, Methodology. **Pascal Sockeel**: Conceptualization, Funding acquisition, Methodology. **Yannick Courbois**: Conceptualization, Funding acquisition, Methodology, Writing – review & editing.

Data availability

The de-identified datasets reported and analysed in this manuscript are available at https://osf.io/vq8cf/?view_only= 0410e2a44f0f41d4aee1a9a6b821384e

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Declarations of interest

None.

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