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NON-ROUTINE PROBLEM SOLVING PERFORMANCE BY COUNTRY ORIGIN

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Abstract – Complexity surrounding a task can hide information being critical to efficiently solve the problem [1]. Non-routine tasks are considered to be of increasing importance in modern workplaces and can be considered complex problems [2]. Non-routine problem solving (NPS) refers to overcoming routine in order to update a wrong mental model and efficiently solve a complex problem, which has shown to be a mental challenge [3], [4]. Only 19 out of 199 participants solving the non-routine task “Flag Run” during an online experiment showed high NPS performance [4]. 28 out of 262 US-American participants showed high NPS performance during a second experiment [3]. In order to research possible correlations between cultural “uncertainty avoidance” [5] and NPS performance, country origin was further diversified. 17 out of 290 Indian participants, and 12 out of 51 German participants were NPS performers. Sex and age were not significant for NPS performance in all country groups. Several highly significant differences between country-origin (India, US-America, Germany) and NPS performance were found.

Keywords – Complex Problem Solving, Mental Model, Overcoming Routine, Non-Routine Task

I. INTRODUCTION

“Ill-Defined problems” lack information on how to clearly solve them or do not provide an instruction on how to handle them effectively [6]. Novices facing some problem will naturally lack necessary knowledge and information to handle the task at hand. In such cases the problem is “undefined” and not “ill-defined” [7]. Ill-defined problems can be regarded as “complex problems” and the attempt to solve them are regarded as “complex problem solving” [8]. Most real life problems are “ill-defined” problems [9], and economic work- [10] and decision-making environments [11] are embedded in a volatile, uncertain, complex and ambiguous domain. Expert knowledge is considered to be of great importance when reducing uncertainty [12] and cognitive processes dealing with complexity benefit from investing time on reflecting about the problem at hand, measured as “response time” [13], to overcome decision biases [14]. Response times are good predictor when strategic uncertainty is in play [15], which was also confirmed by conducting the online experiment “Flag Run” [3], [4]: “The experiment is designed as a puzzle game, consisting of ten levels. The goal is indicated with a green space and flag, (…). The playing piece always moves to the left and is therefore only controlled by the number buttons, not by the directional buttons. This relevant information to control the game is hidden, making it a complex problem-solving task. Knowledge about the true rules has to be acquired by exploration. No change in rules will be implemented; only structural changes will be implemented. These structural representations are called levels. We expect participants to build up and act upon a strategy to solve the puzzle that suits the solving of early levels, which deviates from the true rules governing the game. In later stages, participants will be confronted with uncertainty, as their former and biased strategy will fail to be effective in controlling the game. The game was designed that it was likely for participants to develop a routine during levels 1 to 6, which they had to overcome in order to effectively control the „non-routine” levels 7 to 10.” [3].

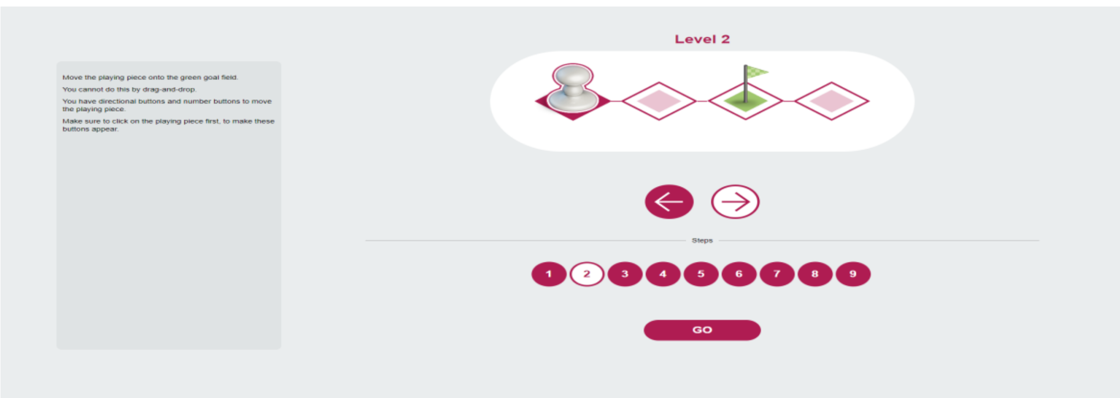

Fig. 1 Frontend “Flag Run” example (own source).

II. RESEARCH QUESTION

"Flag Run" measures non-routine problem solving (NPS) performance, showing highly significant correlations with response time, being (U (19,180) =1052.5, z = -2.755, p=0.006) and (U (28,234) = 1841, z = -3.794, p = 0.000). Only 9.55 % out of 199 mixed-country participants [4] and 10.69 % out of 262 US-American participants were able to overcome their routine and perform well in NPS.

While the studies Chlupsa & Strunz (2019) and Strunz & Chlupsa (2019) failed to find correlations between self-reported 5-dimensional curiosity [16] and NPS performance, literature strongly suggests that such a correlation exists with "uncertainty avoidance" researched by Hofstede. In order to obtain more data on NPS performance by country origin, a third major "Flag Run" experiment including participants via Amazon Mechanical Turk with country origin being India and Germany had been conducted.

Ultimately the research question is, whether cultural uncertainty avoidance links to NPS performance. Behavioral differences in complex problem solving stemming cultural differences between US-American and Indian participants had been found, where the former showed medium uncertainty avoidance values and the latter low uncertainty avoidance values; Germans have been found to show high levels of uncertainty avoidance [17].

Cultural differences are expected to be more visible during complex problem solving (CPS) as it requires causal cognition, which is influenced by the cultural learning environment [18]. Legacy data by US-American "Flag Run" participants are compared to new data by Indian and German participants. It is assumed that low levels of uncertainty avoidance lead to a lower willingness to overcome routine when being faced by uncertainty stemming from unexpected feedback.

During "Flag Run" participants with Indian country origin are considered to show the lowest proportion of NPS performers, due to potentially low levels of uncertainty avoidance and participants with German country origin are expected to show the highest proportion of NPS performers, due to potentially high levels of uncertainty avoidance. US-American are expected to fill the middle ground due to speculated medium uncertainty avoidance levels. Whether reflection on a non-routine task, measured as response time during "Flag Run", can be linked to levels of uncertainty avoidance and whether participants' country origin can be linked to the assumed cultural learning environment remains mostly speculative.

Based on the theoretical background and former experimental results, country origin (Indian, German, US) is expected to be of significant relevance to NPS performance, due to reflection time when facing unexpected feedback relying on uncertainty avoidance.

III. METHOD

Using the online experiment "Flag Run" participants are induced a wrong mental model of the true rules governing the game mechanics during the first six experiment levels. From level seven to level ten participants' behavior is analyzed whether they were able to overcome their induced mental model, and routine strength to adapt their strategy by reflecting and obtaining hidden rules.

Hidden rules include: i) the playing piece always moves left ii) jumping from the left to the right edge of the playing field and iii) the direction buttons do not come with any function other than changing color when being pressed. With each level the experiment's complexity rises, and when no hidden rules are found, the perceived difficulty also rises with each level.

The experiment's software framework "Curiosity IO" automatically save every input, with an attached time-stamp.

IV. PARTICIPANTS

Two hundred ninety (290) Indian and fifty-one (51) German Amazon Mechanical Turk freelancer data were analyzed, and compared with US-American legacy data. Both Indian and German MTurk participants had to fulfill a "HIT approval rate" of greater than or equal to 99 % to ensure highest data quality.

Literature suggests HIT approval rate of at least 95 % [19], and using Amazon Mechanical Work as a recruitment tool has been found to produce data comparable to traditional methods [20]. Country origin sample sizes between Indian/US and German groups differed greatly, as most freelancers are US-American or Indian, with much less Germans being active.
Indian and legacy sample sizes were greater than the required sample size of 180, as much greater data loss, mainly due to connection problems, was expected. Inter- and intra-country analyses with US-Americans, Indians and Germans were conducted.

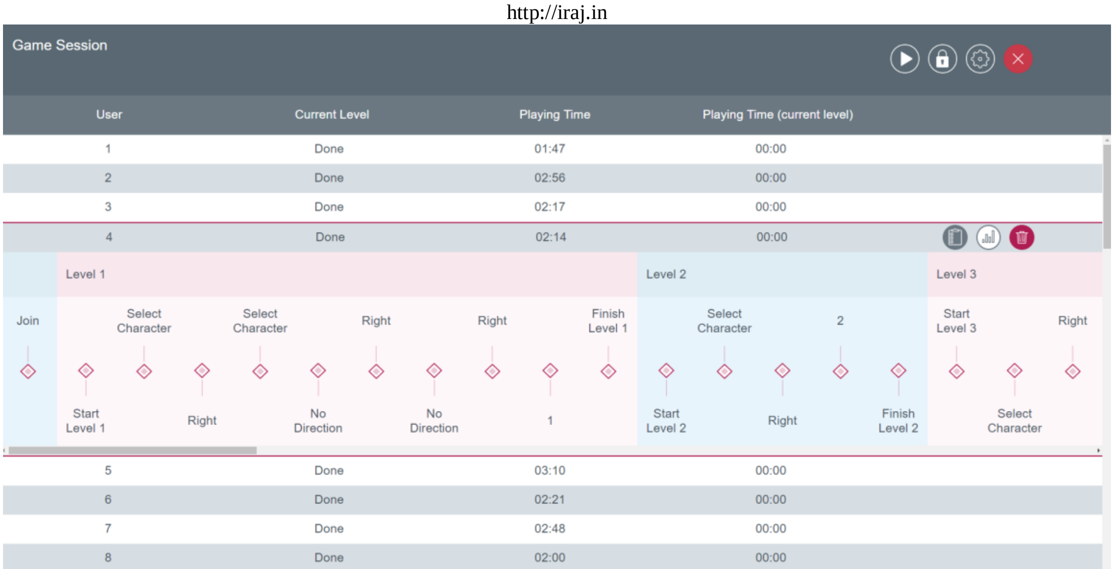

Fig. 2 Backend "Flag Run" example (own source).

V. RESEARCH DESIGN

Amazon Mechanical Turk freelancers (MTurks) participated by entering the provided URL and session code, upon which they were asked to self-report their age and sex. Participants were then forwarded to the frontend of the game, starting with level one and its instructions:

"Move the playing piece onto the green goal field. You cannot do this by drag-and-drop. You have directional buttons and number buttons to move the playing piece. Make sure to click on the playing piece first, to make these buttons appear."

Participants were not provided more detailed instructions in order to avoid deception, which must not be used in behavioral economics [21], [22]. For example, any information regarding the directional buttons would deceive the participant into thinking that the directional buttons came along with some functionality. Participants do not actually see the playing piece moving and are only provided with the output state: participants only see the start and end position of the playing piece. The experiment consists of ten levels. Each level comes with either two, three, four, six or nine playing spaces. In order to complete a game stage, the participant was instructed to place the playing piece on top of the indicated goal field. Several GUI elements can be used to make the playing piece move. The directional buttons do not influence the playing piece at all however. Its direction is always preset to being "left". Therefore, the playing piece can only be moved via the "amount of steps" buttons. Their functionality has to be understood by the participants themselves. This learning process is guided by three different modes: "Semi-Forced", "Free-Choice", and "Pre-Setup".

During the first three game stages, the Semi-Forced game mode is active. It requires the participants to do at least four inputs for one action. An input is a click on the playing piece, direction button, number button and "GO" button. All stages during Semi-Forced mode hide direction and number buttons. The participant has to click on the playing piece first, to make the direction buttons appear. After having clicked on one of the direction buttons, the number buttons appear. When the player click on a valid number button, the "GO" button appears. By pressing "GO" with a valid number button being selected, an "action" is completed. During Semi-Forced mode, an action therefore consists of at least four inputs: one click on the playing piece, one click on any direction button, one click on a valid number button, and one click on "GO". Number buttons were always appearing with integers ranging from 1 to 9. A valid number button, holding some integer "i" during a stage with some number of playing spaces "p", is any such number button where "i" is smaller than or equal to "p - 1". For example, during stages with two game spaces visible, only the number button with integer "1" is valid. When no valid number button is chosen or when an already selected valid number button is unchosen, the "GO" button is not visible. This was implemented in order to avoid the playing piece to go "in circles", as no "progress" would then be visible. With this rule implemented, the playing piece's end position is never the start position. Even though the participant was forced to press a direction button during Semi-Forced mode, the participants are still given a chance to find out that the direction buttons do not actually work. The participant can click on an already selected direction button at any time, seemingly "deactivating" it, as it changes its colors back to its default state. The player can still press "GO" with no direction button "being selected".

During game stages four to six, Free-Choice mode is active. During this mode, participants were provided both direction buttons and number buttons at the same time, after having clicked on the playing piece. During Free-Choice mode, an action therefore consist of at least three inputs: one click on the playing piece, one click on a valid number button and one click on “GO”. During this mode, the player is not any longer “forced” to click on a direction button anymore. Due to induced routine strength and a wrong mental model of the experiments functionality, almost all participants still click on a direction button. The last four game stages are being played in Pre-Setup mode. During this mode the playing piece is already pre-selected, and all GUI elements including directional buttons and number buttons are visible. During Pre-Setup mode, and action consists of at least two inputs: one click on a valid number button and one click on “GO”.

Measurements regarding NPS performance are only done during Pre-Setup mode. The first six stages are designed in such a way that distances from the playing piece starting position to the goal space are equal from the left and right. The playing piece will therefore reach the goal space even when participants have a wrong mental model of the game’s functionality, i.e. trying to make the playing piece move to the right. During game stages five on six the playing piece’s starting position is right-hand of the goal space, inducing the wrong mental model that making the playing piece move to the left is actually done by pressing the “left direction button”. In all first six game stages the level’s design will enhance chances that participants are provided with feedback that feeds the confirmation bias “the directional buttons do work”, inducing routine strength. Level seven is the first game stage where the distances are unequal, and during all Pre-Setup stages the playing piece is positioned left-handed of the goal field. This enables the experimenter to measure whether or not a player is using an action based on “true hidden rules”. This is done by analyzing “action-states”.

Throughout the last four levels, “action-states” are assigned to the participant’s action to analyze progress in learning. Each “action-state” is generated by i) the relative position of the playing piece to the goal space (left or right of goal space), ii) last directional input (left, right, no direction) and iii) the last number input (1-9) which lead to an action. 12 different “action-states” are possible. They are roughly sorted by how close the participants’ understanding of the rules are to the real rules of the game. All stages can be solved in one single action. Any action that does not bring the playing piece on the goal field is considered an action deviation. Depending on the mode the level is played in, two to four inputs are at least required to solve the level, but during Pre-Setup mode all stages can be solved with two inputs. Any further inputs are regarded as an input deviation. In addition, inputs that are not part of the resulting action are saved separately. Each step to solve a level is considered an action. An action can be considered as the output of a function requiring three variables. These variables are the relative position of the playing piece to the goal space (left-handed or right-handed), direction input (left, right, none) and whether or not the number of steps brought the playing piece to the goal space, if the direction was actually influenced by the chosen direction button (“W” or “R”); if no direction was selected the direction “left” is assumed. By this definition, 12 possible actions exist. These actions were saved as an integer, ranging from 1 to 12. Each action was assigned an “action-state”. There are 5 distinguished action-states, being “framed logic”, “random”, “experimental”, “realize” and “king”. Action states were only constructed from data of level 7 to 10. Figure 3 shows the logic behind the action-state analysis.

Multiple input combinations can lead to an action solving the level, which are considered to be a “random” success. With the playing piece being positioned left of the goal space, the player committing a “right-direction” input and choosing the number of steps which would lead to the level being solved, if the direction of the playing piece was actually influenced by the directional buttons in an intuitive way (directional input “right” + number of steps “R”), the action is assigned the “framed logic” action-state. Any other combination of inputs leading to an action, which does not solve a level, is considered an “experimental” action-state (any directional input + number of steps “W” or “R”). If the playing-piece was right-handed before solving the level and the action consisted of the directional input “left” and a “correct” number of steps (number of steps “R”), it is assigned the action-state “random”. This is because the participant might either still believe that the playing-piece can be moved to the left or might believe that the playing-piece can only be moved to the left and that the directional button still has to be pressed anyways. Both believes are wrong but the latter is considered to be closer to the true underlying rules. However, it is impossible to distinguish between these two “belief sets” in this constellation and the player therefore is unable to prove to the experimenter, which of these “belief sets” are followed, when still using a directional button. Therefore, we consider these actions as being solved randomly, assigning the action-state “random”. This also applies to a right-handed constellation, the directional input “right” and a “correct” number of steps (number of steps “R”).

With a left-handed position, the directional input “left” and “R” number of steps, the action is assigned the “realize” action-state, if all remaining levels are also solved in this manner. In this case the player has proven to have realized that the playing figure jumps edges and only goes one way. If following levels include “framed logic“, or “experimental” actions however, it still is assigned “random”. Any left- or right-handed solving action with directional input “none” and “R” number of steps is also assigned “realize” when all remaining levels are solved with “realize” actions. In this case, the player has proven to have realized that the playing-piece is not manipulated by the directional-buttons at all and that the playing-piece is jumping edges.

All consecutive levels solved by single “realize” actions are assigned the action-state “king”. Participants who solved one or more levels with a „king” action were regarded as being part of the group who understand the “true rules” of the game, while all other participants were regarded as being part of the group who failed to obtain “true rules” (true rule knowledge/rule knowledge). Since many players throughout dozens of experiments effectively solved Pre-Setup game levels with the playing stone positioned left of the goal field, choosing direction “right” but counting steps to the left, it is assumed that those participants thought that the “direction buttons” are merely switched, having understood that the playing piece jumps edges. For this reason, action “3” was included to be part of potential “realize” and “king” actions.

Playing stone left of goal field						**Playing stone right of goal field**					
Direction: left		Direction: none		Direction: right		Direction: left		Direction: none		Direction: right	
R	W	R	W	R	W	R	W	R	W	R	W
10	**1**	**11**	**7**	**6**	**3**	**9**	**2**	**12**	**8**	**5**	**4**

If distance and direction, assuming direction could actually be manipulated, led to goal field = R.

If distance and direction, assuming direction could actually be manipulated, would not lead to goal field = W

If Direction: none, = R when distance leads to goal field, = W when not.

1. Actions which do not result in completion of level:
   6 = framed logic
   1, 2, 3, 4, 5, 7, 8 = experimental
2. Actions leading to completion of level:
   1, 2, 4, 5, 6, 7, 8 = random
   9 = random
   3, 10, 11, 12 = random, when not all following levels are completed in one action
   3, 10, 11, 12 = realize, when all following levels are completed in one action
   3, 10, 11, 12 = king, when previous level was solved in one action and/or all following levels are solved with a 3, 10, 11, or 12 in one action

Fig. 3 action states and their categories (own source).

VI. RESULTS

Out of 290 Indian participants, 17 showed high NPS performance by obtaining hidden rules, overcoming their routine strategy, which equals 5.86 % of Indian participants. Out of 51 German participants, 12 showed high NPS performance, which equals 23.53 % of German participants. No significant difference between women and men regarding NPS performance was detected in both country groups: (U(16, 270) = 1813, z = -1.317, p = 0.188) and (U(12, 37) = 205, z = -0.547, p = 0.585).

Age shows no significant difference in both country groups as well: (U(17, 271) = 1705.5, z = -1.807, p = 0.071) and (U(12, 39) = 229, z = -0.111, p = 0.912).

The total average response time per action from level 7 to 10 between participants who obtained hidden rules, and who did not, is highly significant for both country samples: (U(17, 273) = 364, z = -5.832, p = 0.000) and (U(12, 39) = 105, z = -2.865, p = 0.004).

Response time during level 10 is the best indicator for whether a participant tried to solve this level by using logic, derived from having obtained hidden rules, or by using fast and biased strategies – participants who obtained hidden rules, such as the fact that the playing stone jumps edges from left to right, show higher response times per action, as they are counting playing spaces to solve the level in one correct move.

In the Indian country sample, those who obtained hidden rules showed an average response time of 12.41 seconds in level 10 (SD = 3.59 seconds) and those who failed to obtain hidden rules showed an average response time of 4.40 seconds (SD 2.21 seconds).

In the German country sample, those who obtained hidden rules showed an average response time of 11.33 seconds in level 10 (SD = 2.42 seconds) and those who failed to obtain hidden rules showed an average response time of 5.32 seconds (SD = 1.93 seconds).
Therefore, Indian and German behavior is comparable to legacy data stemming from the US-American sample [3], and from the mixed-country sample [4], concluding intra-country analysis. Inter-country analysis used a nonparametric test for three independent samples, including 290 Indian, 262 US-American and 51 German participants, in sum being 603 participants.

The total average response time per action from level 7 to 10 remained highly significant with all 603 participants, comparing 57 NPS performers and 546 non-performers: (U(57, 546) = 5644, z = -7.924, p = 0.000). Significant differences between participants who obtained (NPS performers) and failed to obtain hidden rules by country-origin was found, using the Mann-Whitney U: (U(57, 546) = 11563.5, z = -3.557, p = 0.000). As Indian and US-American sample sizes are comparable, another Mann-Whitney U test was performed by country-origin and average response time from level 7 to 10, showing high significance: (U(290, 262) = 31793.5, z = -3.312, p = 0.001).

Kruskal-Wallis H shows highly significant difference by country-origin with total average response time per action from level 7 to 10: (H(290, 262, 51) = 11.362, df = 2, p = 0.003). Average Indian response time per action from level 7 to 10 was 6.20 seconds (SD = 3.07 seconds), with a span of 31.94 seconds. Average US-American response time per action from level 7 to 10 was 6.64 seconds (SD = 2.58 seconds), with a span of 21.83 seconds. Average German response time per action from level 7 to 10 was 6.41 seconds (SD = 2.05 seconds), with a span of 9.67 seconds. Kruskal-Wallis H shows highly significant difference when comparing country-origin with average response time during level 10: (H(290, 262, 51) = 56.435, df = 2, p = 0.000).
Indians reported an average response time during level 10 of 4.87 seconds (SD = 2.98 seconds), with a span of 20.64 seconds. US-American reported an average response time during level 10 of 6.61 seconds (SD = 4.45 seconds), with a span of 38.63 seconds. Germans reported an average response time during level 10 of 6.75 seconds (SD = 3.28 seconds), with a span of 14.43 seconds.
Kruskal-Wallis H shows significant difference by country-origin and average response time per action in all Pre-Setup levels 7, 8 and 9: (H(290, 262, 51) = 11.998, df = 2, p = 0.002), (H(290, 262, 51) = 6.956, df = 2, p = 0.031) and (H(290, 262, 51) = 27.684, df = 2, p = 0.000).
Kruskal-Wallis H shows significant difference by country-origin and number of NPS performers: (H(290. 262, 51) = 16.614, df = 2, p = 0.000).

VII. DISCUSSION

Indian NPS performance proportion of 5.86 %, with a sample size of 290, were the lowest. US-American NPS performance proportion of 10.69 % with a sample size of 262, filled the middle ground. German NPS performance proportion of 23.53 %, with a sample size of 51, were the highest. Response times were, again, of high statistical significance in all country groups, when groups who succeeded and who failed to obtain hidden rules are compared. Especially results from level 10 had shown that those who obtained a hidden rule were investing in using effective logic, rather than quick and inefficient strategies. Sex and age were not significant for NPS performance in any country group. However, NPS performers were found to significantly differ by country-origin.

Several significant country-origin differences were obtained. Response time during levels were NPS performance was measured differed significantly by country-origin. This was true for each individual level and all levels in total. The number of NPS performers was also found to significantly differ by country-origin.

VIII. CONCLUSION

The results contribute for better understanding of cultural differences and similarities in complex problem solving. In all country samples, neither sex nor age did predict NPS performance. Cultural differences such as uncertainty avoidance might explain NPS performance proportions and response times. The author highly encourages further research to be done, in order to find possible relations between non-routine problem solving performance and uncertainty avoidance, potentially stemming from heterogeneous learning environments.

IX. FUTURE OUTLOOK

While the possible correlation of NPS performance and cultural uncertainty avoidance still remains unclear, latest insights from behavioral economics strongly suggests that such a correlation might be found with “working memory capacity” (WMC). “WMC is generally considered as a trait of an individual in relation to their ability to engage and use their working memory system.” while working memory “refers to the functioning of the multiple component system proposed by Baddeley and Hitch (1974) [which] defines working memory as the mental workspace used for short-term storage and manipulation of information required for diverse cognitive tasks." [23, p. 186]. Decision performance facing complexity might be mediated by WMC in "basic and deeps ways" [24, p. 31], and WMC correlates significantly with "insight-problem solving" [23, p. 214]. Insight problem solving refers to puzzles "where initial approaches to a solution need to be overcome" [23, p. 205]. "Flag Run" can be regarded as an insight problem, as the initial routine induced during level 1 to 6 has to be overcome by level 7 and above. WMC performance can be measured by the "complex span task" [25], [26], which was also designed in a more time-saving variation to save administration time for experimenters [27].

Due to the growing importance of decision-makers being able to quickly adapt their strategy to influences of environmental change, by overcoming implicit motives, personal bias and routine strength, we highly encourage researches to strengthen insight on the possible correlation between NPS performance, uncertainty avoidance and WMC, which can be measured with low resource demands by e.g. "Flag Run" and Foster et al. (2014) shortened complex span task.

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