

Effects of Overloading Command Capacity of Multiplexed FastTap Menus on Spatial Learning in Tablets

Sayeem Md Abdullah^a and Md. Sami Uddin^b

Department of Computer Science, University of Regina, Regina, Saskatchewan, Canada

Keywords: Command Selection, Spatial Memory Development, Menu Design, Tablets, Multi-Touch.

Abstract: Multiplexing can overload the command capacity of spatially stable tablet menus like FastTap by overlaying multiple tabs of commands. While multiplexed menus can facilitate spatial learning and quick command selections with a limited number of commands (20 items per tab), it is unclear whether multiplexed tablet menus support spatial learning as the capacity of each tab increases. To that end, we conducted a controlled study with four tab-based FastTap menus and investigated spatial learning in three sizes of tabs: Small (16 commands per tab), Medium (30), and Large (42). Results indicated that participants developed spatial memory of commands in all conditions; however, the spatial memory development rate significantly slowed down when the menu size grew. We discovered a reverse correlation between command capacity and spatial memory development in multiplexed contexts, which could guide the design of future spatial memory interfaces for tablets with increased command capacity.

1 INTRODUCTION

Multi-touch tablets require users to find and select command locations, similar to any Graphical User Interface (GUI). Spatial memory, which helps us learn real-life locations, can be leveraged to design interfaces that support rapid command selection (Postma & De Haan, 1996). By displaying command icons in fixed locations, spatial memory-based GUIs can facilitate quick learning of command locations. Research has shown that spatial memory techniques can outperform popular command-selection tools such as Ribbon menus, hierarchical menus, or Marking Menus when using smaller command sets (Gutwin & Cockburn, 2006; Mollashahi et al., 2018). However, modern desktop GUIs like Microsoft Office and Adobe Photoshop typically include hundreds of commands in their menus, often unseen on tablets. Moreover, displaying a large command set on tablets can be difficult as they may slow down the finding and selecting commands.

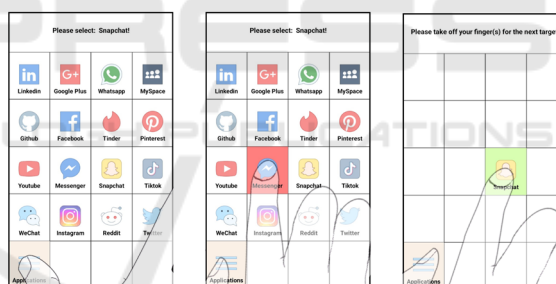


Figure 1: Command selections with FastTap. From left: invoking a menu by pressing the menu button with the thumb - *novice selection*; invoking the menu (thumb) and incorrect command location (index); pressing the menu (thumb) and correct command location (index) together without invoking the entire menu - *expert selection*.

One reason for this difficulty could be the small size of handheld devices, which may have made it challenging to include many commands. Part of the reason is that we know little about how increasing the command capacity of tablet menus affects finding and selecting commands. To address one aspect of this problem, Gutwin et al. (2014) developed a rapid

^a <https://orcid.org/0009-0008-3324-5609>

^b <https://orcid.org/0000-0001-8354-2320>

command selection technique called FastTap Menu for tablets (see Figure 1).

They used a 5x4 grid to display 19 commands, with one cell reserved for a menu button. Users could access the commands by pressing the menu button with their thumb and selecting an item with their index finger while still pressing the menu button with their thumb. Once learned, they could quickly execute commands by combining menu invocation and command selection into a thumb and index finger tap. However, this menu had only 19 commands. Lately, Abdullah & Uddin (2024a, 2024b) explored increasing grid size to expand command capacity of FastTap, and found that the larger grid could impede spatial learning of commands.

In an effort to expand the command capacity in tablets, Gaur et al. (2018) multiplexed the menu area of FastTap. Their design used a tabbed layout with four overlaying tabs, each containing a 20-item grid, similar to the original FastTap design (Gutwin et al., 2014). While results suggested that multiplexing could potentially increase the command capacity of FastTap Menus, it can create an additional level of difficulty for learning and recalling command locations. It is because each location in a multiplexed menu contains multiple commands, overlaying on top of each other, separated by tabs. Moreover, no prior research explicitly explored the effect of overloading command capacity on the development of spatial memory. Without this knowledge, it would be difficult to design better tablet interfaces that have approximately 1.14 billion users worldwide (*Mobile App Statistics Everyone Should Know in 2023*, n.d.).

Therefore, we conducted a study to test how increasing command capacity affects spatial learning when spatial memory was multiplexed with four tabs within the FastTap Menus. During the study, participants completed command selection tasks in three different sizes of multi-tab FastTap menus: Small (16 commands in one tab), Medium (30) and Large (42). Small, medium, and large interfaces had 64, 120, and 168 commands, respectively, in total. Key results from our study were:

- Users developed spatial memory of commands in all interfaces; however, spatial learning significantly impeded (increased completion time and errors) when the menu grew;
- Although expert selections increased notably over time, there was no difference in expert selections across the three interfaces;
- Multiplexing spatial memory had fewer interferences on learning, but interferences increased with larger menus;

- Participants found interfaces more challenging as menu items grew and preferred smaller.

Our research contributes several novel insights into spatial learning in tablets. First, we conducted the first study exploring how overloading command capacity in multiplexed tablet menus impacts spatial learning of commands. Second, we demonstrated that users could develop spatial memory of commands regardless of the command set size in multi-tab tablets. However, we noticed a significant slowdown in command finding and selecting performance as the grid size increased. Lastly, our findings of the negative correlation between menu multiplexing and spatial learning can inform the design of future tablet menus employing spatial memory multiplexing to expand command capacity.

2 RELATED WORKS

2.1 Spatial Memory in GUIs

Spatial memory is one basic human ability that supports learning and remembering information about one's surroundings and spatial orientation (Kessels et al., 2002; Postma & De Haan, 1996). Researchers have examined the development of spatial memory (Postma & De Haan, 1996; Thorndyke & Goldin, 1983). According to Siegel et al.'s model (1975), spatial memory consists of three types of knowledge: landmark, route, and survey. Initially, people develop landmark knowledge through visual search (Hasher & Zacks, 1979). As they become more familiar, they acquire route knowledge (Thorndyke & Hayes-Roth, 1982), which then evolves into survey knowledge, enabling them to recall information from memory.

Following real-life, the process of learning and recalling information in GUIs usually involves three stages: cognitive, associative, and autonomous, as identified by Anderson (2000) and Fitts and Posner (1967). During the cognitive stage, users acquaint themselves with an interface and visually search for commands. Then, in the associative stage, they memorize commands and begin to retrieve them from memory, although some visual searching may still occur. Later in the autonomous stage, users can recall commands without searching.

Researchers have utilized spatial memory in GUIs to assist users in locating and selecting commands quickly (Cockburn et al., 2014; Kurtenbach & Buxton, 1994; Zheng, Lewis, et al., 2018). Scarr et al.'s (2014) CommandMaps for instance, present all commands in spatially fixed locations in desktop GUIs, facilitating

faster retrieval, even for realistic tasks. Similarly, Gutwin et al.'s (2006) ListMaps and Cockburn et al.'s (2006) Space Filling Thumbnails have shown that stable and flat menus can substantially improve item revisitation performance in various contexts.

Spatial memory also enhances interactions on multi-touch devices. Gutwin et al.'s (2014) FastTap Menus use a stable flat grid menu on tablets, allowing rapid command selection by combining thumb and index finger actions. Similar methods relying on spatial memory have been shown to enhance selection speed on tablets (Gaur et al., 2018; Gutwin et al., 2014; Uddin & Gutwin, 2016), smartwatches (Jannat & Hasan, 2023), smartphones (Zhai & Kristensson, 2003; Zheng, Bi, et al., 2018), and tabletops (Uddin et al., 2016). Moreover, studies indicate that spatial memory provides benefits in large environments such as VR (Gao et al., 2019), wall display (Jansen et al., 2019), and even in touch tables (Joshi & Vogel, 2019). However, these studies do not explore how varying menu sizes affect the development of spatial memory.

2.2 Expanding Command Capacity in Handheld Devices

Researchers explored various methods to increase the command capacity of smartphones and tablets while maintaining fast command selection speed. One general approach was to use memory-based mechanisms. For instance, Gutwin et al.'s (2014) FastTap Menus employed a fixed grid to show 19 commands in tablets. An updated version of FastTap expanded its capacity to 24 commands (Gutwin et al., 2015). Abdullah & Uddin (2024a, 2024b) showed that FastTap could hold up to 56 items by altering the grid size and compromising spatial learning performance. Another memory-based work by Schramm et al. (2016) used a hidden bezel toolbar to display 28 commands on tablets. Uddin et al. (2016), however, relied on users' proprioceptive knowledge of hands to display 20 commands around the spread-out fingers of a hand in tablets.

Using gesture-based methods was another way to increase menu capacity on smaller devices. For example, multi-touch marking menus (Lepinski et al., 2010) can include about 64 commands. M3 gesture menu (Zheng, Bi, et al., 2018) explored position-specific gestures to overload command capacity. Even augmented reality was investigated to virtually display commands around smaller handheld devices, which could accommodate a large set of commands in a 46x27 grid (Hubenschmid et al., 2023).

Many people tried to increase command capacity by using multiplexing menu space. For instance, Gaur

et al. (2018) significantly enhanced the command set size of FastTap menus to 80 commands by multiplexing the display space with four tabs, each containing 20 commands. Uddin et al. (2016) multiplexed the space between the index and thumb to accommodate 80 commands with four tabs in tablets. Even smartwatches can use multiplexing to display up to 9 commands in a 3x3 grid (Lafreniere et al., 2016). While multiplexing may overload the capacity of FastTap, we still lack an understanding of how it impacts the recall and learning of commands across different sets. Thus, we intend to investigate the influence of multiplexing on spatial learning.

3 STUDY INTERFACES

We aimed to explore how the increasing capacity of commands influences the development of spatial memory in menus with multiple tabs. Gaur et al. (2018) extended the FastTap menu (Gutwin et al., 2014) by including four tabs and demonstrated that multiplexing could be an effective way to overload the menu capacity of tablets.

We adapted Multi-tab FastTap menu to design three prototype interfaces with three grid sizes: Small (5x4), Medium (7x5), and Large (8x6), where we used the bottom row for menu buttons (see Figure 2). Following the original design, four cells of the bottom row (starting from the left) were assigned to four tabs; each tab could be accessed by tapping the respective tab activation button. The rest of the bottom row was blank. So, our three menus contained 16, 30, and 42 commands in each tab, respectively.

We used an 8.7-inch tablet (Samsung Galaxy Tab A7 Lite) to implement our interfaces. Following Gaur et al.'s (2018) Multi-tab FastTap and Parhi et al.'s (2006) guide for touch target size, we initially designed four grids, 5x4, 7x5, 9x6, and 11x7, with 64, 120, 192 and 280 items in total, respectively. During a pilot study, people faced difficulty reaching the targets displayed in the upper row, as our device was larger than the original (8.7-inch instead of 7). Also, people took significantly more time in the 11x7 grid. So, we removed the 11x7 grid and reduced the Large grid size to 8x6. Also, we reduced the grid height by ~1.7 inches from the top (that displayed target questions) to ~7 inches, matching the original design.

So, in this study, we had three conditions (each with four tabs), where each tab in the Small condition had 16 items, resulting in a total of 64 items. The tabs were arranged from left to right in the order of Finance, Drinks, Clothing, and Applications.



Figure 2: Study interfaces with highlighted target locations. From top: Small (5x4), Medium (7x5) and Large (8x6).

Similarly, Medium had 30 items in a tab, and overall, 120 items, arranged in Transport, Household, Beauty, and Produce tabs from left to right. The Large condition included 42 items, resulting in 168 items in total, organized in Academics, Flags, Fictional, and Animals tabs, from left to right (see Figure 2).

4 STUDY METHOD

4.1 Tasks and Stimulus

In the study, participants selected a series of targets that appeared at the top of the grid. Selection methods were similar to FastTap (Gutwin et al., 2014), thumb and index finger actions (see Figure 1). The default

setting concealed the commands, requiring a 200ms press on the menu button with the thumb to reveal them. Subsequently, users could select commands with their index finger. Our interfaces supported expert and novice selections (Gutwin et al., 2014). If users know the menu, they can quickly select a command without waiting 200ms for the whole menu to display: an *expert* selection. Otherwise, users could wait to see the entire menu and perform a visual search for the command before selecting it: a *novice* selection. Selection feedback was provided by changing the selected cell's background to green for a correct selection; otherwise, it was red. Users could move to the next target only after a successful selection. They also had to lift their thumb from the screen to progress to the next target question.

For the study, we selected four targets as stimuli from each tab: one target had no overlap with any other tab, two targets overlapped between two different tabs, and one target overlapped in all four tabs. Among the four targets, one was from the corner, two were from the centre, and another one from the side. This would allow us to determine any interference due to multiplexing. So, in total, sixteen targets were used as stimuli in a condition.

During the study, trials were repeated over eighteen blocks, where after every fifth block, we kept a blind block, where the menu elements remained hidden even after pressing the menu button. The three blind blocks required participants to rely on memory to remember target positions, encouraging people to become familiar with the menu. In total, there were fifteen regular and three blind blocks.

4.2 Procedure and Study Design

We conducted a within-subject study with three conditions: Small (5x4), Medium (7x5), and Large (8x6) grids. Each condition had four tabs, with four different command sets (Figure 2). The study consisted of 18 blocks of trials, where one block included sixteen targets (order randomized). The order of the conditions was balanced using a Latin Square design (Grant, 1948). Participants were instructed to complete tasks with speed and accuracy.

Participants completed a practice session with a 4x3 grid to familiarize themselves with the interface and operations. The practice session included three tabs: Zodiac, Folder, and Music, arranged from left to right. Participants completed 18 blocks of trials, including three blind blocks, with three targets. After completing each condition, participants completed a NASA-TLX questionnaire, and after completing all four conditions, they provided their preferences.

4.3 Participants and Apparatus

Fourteen individuals (twelve Cis men, two Cis women, one left-handed, ages 19-33, mean age 24.21) were recruited from a local university to participate in the study. All were familiar with touch devices, with an average of 9.29 years of experience. Furthermore, the average screen time of participants was 5.46 hours per day. The study session lasted ~60 minutes, and each participant received a \$10 gift card as an honorarium.

All experiments were conducted on a Samsung Galaxy Tab A7 Lite 8.7-inch multi-touch display. The application was developed for Android using Java.

5 RESULTS

Due to technical and operational issues, a few trials needed excessive time to complete. So, we excluded 168 out of 10080 (1.67%) from the regular blocks and 42 out of 2016 (2.08%) from the blind blocks as outliers (3 s.d. away from the means of respective blocks). Shapiro-Wilk tests indicated that our samples followed an approximately normal distribution, confirmed by Q-Q plots. Therefore, we proceeded with ANOVA for our analyses. We report the effect size for significant RM-ANOVA results as general eta-squared: η^2 (considering .01 small, .06 medium, and >.14 large (Cohen, 1973)), and Bonferroni correction was performed for post-hoc pairwise t-tests. We performed Greenhouse-Geisser adjustments on the results of our study (resulting in fractional degrees of freedom), where ANOVA's sphericity assumption was violated (Mauchly's test).

5.1 Trial Completion Time

The trial completion time was calculated from when a target question appeared on the screen to when a user successfully selected the required target. Mean completion times are summarized in Figure 3 for regular and blind blocks (B6, B12, and B18). For regular blocks, ANOVA showed a significant main effect of *condition* ($F_{2,26}=26.87, p<0.001, \eta^2=0.22$).

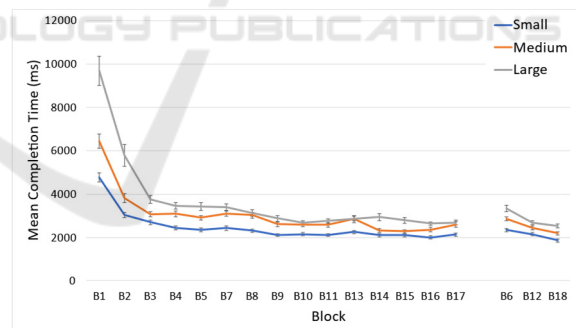


Figure 3: Trial Completion Time (\pm s.e.) by Condition and Block.

Small condition (mean 2463.43ms, s.d.1335.25) outperformed Medium (3039.46ms, s.d. 1992.43), and Large (3654.92ms, s.d. 2818.56). People learned command locations quickly; hence, completion time dramatically decreased across *blocks* ($F_{14,182}=46.96, p<0.001, \eta^2=0.61$). We also found a *condition* \times *block* interaction ($F_{28,364}=8.36, p<0.001, \eta^2=0.22$).

A similar pattern was found in blind blocks, where ANOVA found a significant main effect of *condition* ($F_{2,26}=6.80, p<0.001, \eta^2=0.27$), *block* ($F_{2,26}=35.85$,

$p < 0.001$, $\eta^2 = 0.23$), and *condition* \times *block* ($F_{4,52} = 1.73$, $p = 0.16$) with Small (mean 2114.23ms, s.d. 1137.32), Medium (2492.72ms, s.d. 1304.71), and Large (2840.03ms, s.d. 1676.46). Follow-up tests also showed significant differences between all the conditions for both regular and blind blocks (all $p < 0.001$), indicating consistent results throughout.

Additional analysis on regular blocks by condition and position revealed that there were differences in mean completion time by positions: corner (mean: 2800.39ms, s.d. 2574.22), centre (3074.88ms, s.d. 2387.67) and side (3043.58ms, s.d. 2656.09). ANOVA found an effect of *position* ($F_{2,26} = 16.04$, $p < 0.001$, $\eta^2 = 0.09$), *condition* ($F_{2,26} = 23.24$, $p < 0.001$, $\eta^2 = 0.56$) and *condition* \times *position* interaction ($F_{4,52} = 11.40$, $p < 0.001$, $\eta^2 = 0.15$) on completion time in regular blocks. However, follow-up tests show significant differences between corner:centre and corner:sides only across three conditions ($p < 0.007$).

5.2 Expert Selections

We recorded expert selections when a user selected a target before it appeared on the grid (less than 200ms), irrespective of accuracy. Figure 4 illustrates the results of expert selections in regular blocks.

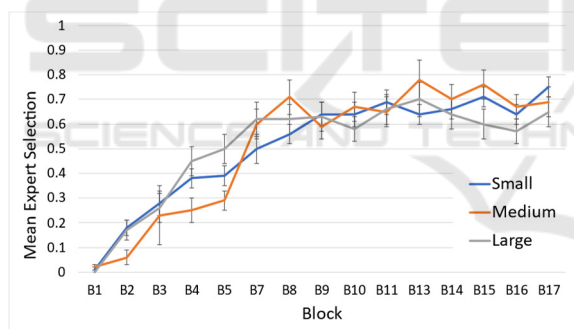


Figure 4: Expert Selection (\pm s.e.) by Condition and Block.

Although expert selections significantly increased over time, *block* ($F_{2,29,29,81} = 11.68$, $p < 0.001$, $\eta^2 = 0.29$), with over 60% expert selections in later blocks, ANOVA showed no effect of *condition* ($F_{2,26} < 0.001$, $p = 0.99$) and *condition* \times *block* interaction ($F_{28,364} = 0.64$, $p = 0.02$). Mean expert selection rates were identical across conditions: Small (mean: 0.51, s.d. 0.62), Medium (mean: 0.51, s.d. 0.85) and Large (mean: 0.51, s.d. 0.80).

Additional analysis shows that out of 9912 successful selections made during regular blocks, 3698 (37.31%) were experts. Among the 1903 erroneous selections, 1439 (75.62%) were erroneous expert selections. When categorized according to the menu size (Small, Medium, and Large), there were

1409, 1180, and 1109 successful expert selections, and 301, 536, and 602 unsuccessful expert selections, respectively. So, the results indicate that larger multiplexed menus could impede performance.

Further analysis by condition and position showed no significant effect of any measures: *condition* ($F_{2,26} = 0.02$, $p = 0.98$), *position* ($F_{2,26} = 2.10$, $p = 0.14$), and *condition* \times *position* ($F_{4,52} = 0.64$, $p = 0.63$), with corner (mean: 0.48, s.d. 0.70), centre (0.54, s.d. 0.86) and side (0.51, s.d. 0.88).

5.3 Errors in Selection

The errors in selection were calculated by the number of incorrect selections before the correct one, which are summarized in Figure 5.

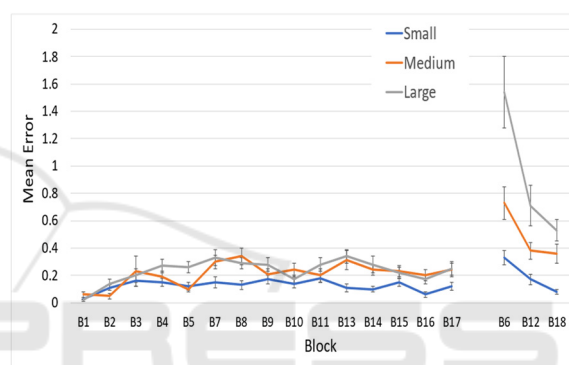


Figure 5: Errors (\pm s.e.) by Condition and Block.

ANOVA showed a significant effect of *condition* on errors ($F_{2,26} = 4.76$, $p = 0.01$, $\eta^2 = 0.06$), with Small being the most accurate (mean errors 0.13, s.d. 0.42), Medium (0.21, s.d. 0.69), and Large having the most errors (0.23, s.d. 0.63). As seen in Figure 5, errors increased slightly in the later blocks, yielding a significant effect of *block* ($F_{14,182} = 4.31$, $p < 0.001$, $\eta^2 = 0.09$). A probable reason could be the reliance on weakly developed spatial memory (due to larger menu sizes) to recall target positions. We found no *condition* \times *block* interaction ($F_{28,364} = 1.04$, $p = 0.42$). Post-hoc pairwise tests showed significant differences between all conditions (all $p < 0.001$) except Medium and Large ($p = 0.12$).

Similar results were found in blind blocks providing significant effects of *condition* ($F_{1,22,15,90} = 4.88$, $p = 0.04$, $\eta^2 = 0.18$), *block* ($F_{1,18,15,31} = 10.47$, $p = 0.004$, $\eta^2 = 0.12$), and *condition* \times *block* interaction ($F_{4,52} = 2.85$, $p = 0.03$, $\eta^2 = 0.05$). Mean errors being the lowest in Small (mean 0.19, s.d. 0.55), Medium (0.49, s.d. 1.22), and the highest in Large (0.93, s.d. 2.40), all pairs being notably different (all $p < 0.002$).

Table 1: Error analyses by condition and overlapped tabs.

	Small				Medium				Large			
	Overall	No Overlap	2 Tabs Overlap	4 Tabs Overlap	Overall	No Overlap	2 Tabs Overlap	4 Tabs Overlap	Overall	No Overlap	2 Tabs Overlap	4 Tabs Overlap
Correct (correct tab & position)	2959 (87.41%)	789 (95.98%)	1443 (85.23%)	727 (83.56%)	2865 (80.42%)	723 (83.39%)	1452 (80.76%)	690 (76.90%)	2771 (78.06%)	729 (84.47%)	1362 (76.27%)	680 (75.46%)
Off-by-1 error (correct tab, 1 pos. off)	315 (9.31%)	25 (3.04%)	179 (10.57%)	111 (12.76%)	408 (11.44%)	79 (9.11%)	197 (10.96%)	132 (14.65%)	475 (13.38%)	62 (7.19%)	265 (14.83%)	148 (16.43%)
Other error (correct tab, >1 pos. off)	43 (1.27%)	5 (0.61%)	26 (1.54%)	12 (1.38%)	125 (3.51%)	24 (2.77%)	67 (3.73%)	34 (3.77%)	148 (4.17%)	27 (3.13%)	74 (4.14%)	47 (5.22%)
Tab error (incorrect tab, correct pos.)	45 (1.33%)	1 (0.12%)	30 (1.77%)	14 (1.61%)	77 (2.16%)	21 (2.42%)	36 (2.00%)	20 (2.23%)	70 (1.97%)	19 (2.20%)	35 (1.96%)	16 (1.78%)
Tab + off-by-1 (incorrect tab, 1 pos. off)	17 (0.50%)	0 (0%)	12 (0.71%)	5 (0.57%)	63 (1.77%)	12 (1.38%)	33 (1.83%)	18 (2.00%)	47 (1.32%)	11 (1.27%)	30 (1.68%)	6 (0.67%)
Tab + other (incorrect tab, >1 pos. off)	6 (0.18%)	2 (0.24%)	3 (0.18%)	1 (0.11%)	25 (0.70%)	8 (0.92%)	13 (0.72%)	4 (0.45%)	39 (1.10%)	15 (1.74%)	20 (1.12%)	4 (0.44%)

We also analyzed the regular blocks based on their condition and position. ANOVA showed no significant effect of *position* ($F_{2,26}=2.10$, $p=0.14$), *condition* ($F_{2,26}=0.02$, $p=0.98$) and *condition* \times *position* interaction ($F_{4,52}=0.64$, $p=0.63$). However, the corner had the most accuracy (mean errors: 1.41, s.d. 0.80), followed by the centre (1.52, s.d. 1.00), and the side had the least accuracy (1.99, s.d. 2.10).

Furthermore, we analyzed the errors in the regular blocks based on different conditions and overlapped tabs, excluding blocks B6, B12, and B18 (see Table 1). Our analysis suggests that participants made more errors in the Large condition than others.

We observed that for tab-related errors, where incorrect menus/tabs were selected but grid-locations of targets were correct or missed by 1 cell, overall, multiplexed spatial menus yielded relatively low errors: less than 4% across three conditions – indicating generally fewer tab-related interferences. However, these interferences increased when the menu size grew. We further noticed that most errors in the study were *off-by-1* (correct tab, 1 pos. off). This means that participants selected the correct tab, but selections were one position off. The least common errors in this category were from *Tab + other* (incorrect tab, >1 pos. off), which is when the participant selected the incorrect tab, and selections were more than one position off. Again, results indicate that these errors also increased when menu sizes increased; Large condition produced the highest number of errors.

5.4 Subjective Responses

We compared the raw NASA-TLX responses for all the conditions (see Table 2).

Table 2: Error Mean (s.d.) effort scores (1-10 scale, low to high; performance reversed, failure to perfect).

	Small	Medium	Large	χ^2_r	p
Mental	5.86 (2.41)	7.36 (2.21)	8.29 (1.59)	26.46	0.01
Physical	4.79 (2.55)	5.29 (2.76)	6.64 (2.24)	30.79	0.004
Temporal	5.57 (2.68)	5.07 (2.59)	7.07 (2.27)	28.30	0.01
Performance	8.43 (1.65)	7.93 (1.69)	7.50 (1.79)	25.29	0.02
Effort	5.93 (1.90)	6.79 (2.19)	7.79 (1.93)	27.87	0.01
Frustration	4.14 (2.80)	5.29 (2.73)	6.14 (3.08)	29.60	0.01

Results indicated a significant difference between all the conditions, with the Large condition having a higher overall workload score than others. Post-hoc tests revealed a significant difference in mental demand between Small and Large conditions ($p=0.01$). However, no significant differences were found in physical, temporal, performance, effort, and frustration across all conditions.

Table 3: Participant preferences among conditions.

	Small	Medium	Large
Speed	8	5	1
Accuracy	6	8	0
Memorization	9	4	1
Expert Mode	5	5	4
Comfort	10	3	1
Overall	3	10	1

Participant preferences are reported in Table 3. Regarding speed, memorization and comfort, at least 57% of participants preferred the Small condition, and out of the two larger conditions, Medium was the second-best preferred menu. In terms of accuracy, interestingly, 58% of users preferred Medium, and the rest chose Small. For expert selection use, 4 people preferred the Large condition. Finally, in the case of overall satisfaction, interestingly, the majority, 71%, preferred Medium over Small.

6 DISCUSSIONS

6.1 Explanations for Results

6.1.1 All Overloaded Menus Enabled Spatial Memory Development

Our analyses indicated that the mean trial completion time decreased across the blocks, as depicted in Figure 3, despite differences in command set sizes. It suggests that people developed spatial memory in all conditions, which can be explained by the three stages of spatial learning (Fitts & Posner, 1967).

Our participants were unfamiliar with the three multiplexed FastTap menus, causing them to spend more time searching for the targets visually. At this time, they were actively engaged in the *cognitive stage* of spatial learning (Fitts & Posner, 1967). Their effortful menu interactions while searching for the targets could also contribute to the spatial learning of commands as a by-product (Cockburn, Kristensson, et al., 2007; Darken & Sibert, 1996). During the study, our participants might have transitioned to the *associative stage* of spatial learning after a short interaction with the menus (Fitts & Posner, 1967). We also observed a dramatic reduction in completion time during the early stages of our study (around 3-5 blocks, as shown in Figure 3). Participants began to utilize more expert selections at these stages (Figure

4). They skipped waiting (200ms) for command icons to appear and instead relied on their memory to recall target locations in all menus. This suggests that participants in our study developed spatial memory for commands across all overloaded menus. Our findings also indicated that participants could utilize their spatial knowledge more effectively and efficiently in smaller menus than larger menus with more items, as demonstrated by completion time and error rate analyses.

6.1.2 Why Did Selection Performance Increase as Time Progressed?

We observed a significant improvement in users' selection performance over time, as evidenced by reduced trial completion time and increased expert selections. We believe FastTap's selection mechanism contributed to this performance growth.

The target selection process involved three steps. First, to invoke the hidden menu, participants placed their thumb on the Menu buttons at the bottom row. Second, when the menu was displayed on the screen, people could visually search for a desired item. Finally, people could use their index finger to select the target while keeping their thumb on the menu. Novice users must follow these three steps to select an item if unfamiliar with the target locations. However, with practice and over time, users could learn the locations of commands and quickly recall them from memory. It allowed them to merge the initial and final steps, skipping the visual search and promptly selecting the target commands (see Figure 1). It is worth noting that novice users in our study also experienced a 200ms delay between the menu button press and the commands display. Expert users, however, could skip this delay by merging menu activation and target selection into a chunked thumb-index action. Though menu sizes varied in our study and involved multiplexing the menu space, this pattern was evident in all three sizes of menus.

6.1.3 Does Multiplexing Large Menus Impede Spatial Learning?

While all menus in our study facilitated spatial memory development regardless of their size, we observed a significant reduction in spatial learning as the menu size increased. We identify two potential reasons behind these findings.

First, the choice-reaction time of Hick-Hayman Law (Cockburn, Gutwin, et al., 2007; Hick, 1952) and the target size of Fitts' Law (1954) can explain the relatively slower target selection speed in larger interfaces. Since the number of commands increased

in larger menus, from 16 to 30 and 42 in one grid, the available choices for users to select from increased (and the size of targets decreased) substantially. In addition, our menus had four tabs, providing additional choices at the tab level. Due to multiplexing, each grid cell included four overlapping commands. As such, people may have spent substantially more time searching for the target locations and correct tab. Additionally, the smaller target sizes in larger menus may have made selection difficult. FastTap enables rapid selections based on spatial memory, but the presence of menu and command choices from multiple large command sets may have hindered its quick development.

Second, people typically rely on landmarks present in GUIs (Uddin & Gutwin, 2021) to learn command locations. In our study, grid lines, corners and bezels of the tablet could work as landmarks and support spatial learning, at least in smaller conditions. However, when the number of commands increased, and menus were multiplexed, existing landmarks may have weakened, as one landmark acted as a reference point for multiple and overlapping items. Our position-specific analyses suggested that people mostly struggled and made more errors with targets located in the centre and side, particularly in larger menus. Using additional landmarks (Uddin, 2022) could improve spatial learning in larger-size menus and could be a future avenue of research.

6.2 Design Implications and Generalizing Results

Our results suggest that participants had difficulty developing spatial knowledge of commands as the menu size increased, resulting in slower selection speed and more errors in larger-multiplexed interfaces. Therefore, designers can rely on multiplexing menu space to increase the command capacity of tablet menus without compromising performance, as long as the grid size remains small. They need to be cautious when overloading the menu capacity. However, in such situations, our results suggest that designers can trade among three regions of a screen: sides, corners, and centre. Although selection performance decreased when menu size grew, we found that targets from the corner region required significantly less time than the side and centre regions. In addition, our results raise the question of whether multiplexing alone is adequate to increase command capacity in menus, particularly with larger command sets. While our results demonstrated the value of multiplexing in enabling spatial learning, as discussed above, the value could

be further enhanced by adding spatial learning support, like landmarks, in larger menus, a route we aim to explore in future.

6.3 Limitations and Future Work

Our research has limitations that we plan to tackle in future. First, following prior research on FastTap, we developed prototype interfaces on an 8.7-inch tablet, maintaining a 7-inch grid size, which yielded promising initial results. Moving forward, we plan to explore multiple avenues. The goals include developing real-world applications, conducting long-term studies, and implementing Multi-tab FastTap Menus across various screen sizes for performance assessment. We plan to integrate this technology into new foldable devices like the Galaxy Z Fold and Google Pixel Fold to improve their capabilities.

Second, to minimize interference among tabs and ensure clarity in distinguishing each tab, we utilized twelve distinct sets of icons (Figure 2). This design aimed to prevent confusion and support learning by providing unique visual references for each tab. The familiarity of these icon sets among participants may have influenced selection performance, as the study used icon names as target stimuli. For instance, participants might find it easier to recognize Animal icons than Fictional icons, potentially impacting target icon search performance. Future research could explore how familiarity influences cognitive strategies, spatial learning, and decision-making processes in similar contexts.

7 CONCLUSIONS

We studied the effect of overloading menu capacity on spatial memory in tablets using multiplexed FastTap Menus with four tabs in three different grid sizes: Small, Medium, and Large, containing 64, 120, and 168 items, respectively. While spatial learning dramatically slowed in larger menus, we found that people developed spatial memory in all multiplexed menus. As the grid size grew, both selection time and errors rose, but participants still effectively used the expert selection mode. Our research provides new empirical evidence showing an inverse relationship between menu capacity and spatial learning of commands. These findings can form the basis for developing future tablet interfaces with extensive command sets by multiplexing spatial memory.

ACKNOWLEDGEMENTS

The work was supported by the Natural Sciences and Engineering Research Council of Canada (RGPIN-2023-04393).

REFERENCES

- Abdullah, S. M., & Uddin, Md. S. (2024a). Revisiting FastTap: Effects of Increasing Command Capacity of Spatial Memory Menus in Tablets. *2024 IEEE 15th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, 0683–0689. <https://doi.org/10.1109/UEMCON62879.2024.10754660>
- Abdullah, S. Md., & Uddin, Md. S. (2024b). Effects of Increasing Command Capacity of Spatial Memory Menus in Tablets. *Companion Proceedings of the 2024 Conference on Interactive Surfaces and Spaces*, 69–72. <https://doi.org/10.1145/3696762.3698055>
- Anderson, J. R. (2000). Learning and memory: An integrated approach, 2nd ed. In *Learning and memory: An integrated approach, 2nd ed.* John Wiley & Sons Inc.
- Cockburn, A., Gutwin, C., & Alexander, J. (2006). Faster document navigation with space-filling thumbnails. *Conference on Human Factors in Computing Systems - Proceedings, 1*, 1–10. <https://doi.org/10.1145/1124772.1124774>
- Cockburn, A., Gutwin, C., & Greenberg, S. (2007). A predictive model of menu performance. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '07*, 627–636. <https://doi.org/10.1145/1240624.1240723>
- Cockburn, A., Gutwin, C., Scarr, J., & Malacria, S. (2014). Supporting Novice to Expert Transitions in User Interfaces. *ACM Computing Surveys*, 47(2), 1–36. <https://doi.org/10.1145/2659796>
- Cockburn, A., Kristensson, P. O., Alexander, J., & Zhai, S. (2007). Hard lessons: Effort-inducing interfaces benefit spatial learning. *Conference on Human Factors in Computing Systems - Proceedings*, 1571–1580. <https://doi.org/10.1145/1240624.1240863>
- Cohen, J. (1973). Eta-squared and partial eta-squared in communication science. *Human Communication Research*, 28(56), 473–490.
- Darken, R. P., & Sibert, J. L. (1996). Wayfinding strategies and behaviors in large virtual worlds. *Conference on Human Factors in Computing Systems - Proceedings*, 142–149. <https://doi.org/10.1145/238386.238459>
- Fitts, P. M. (1954). The information capacity of the human motor system in controlling the amplitude of movement. *Journal of Experimental Psychology*, 47(6), 381–391. <https://doi.org/10.1037/H0055392>
- Fitts, P. M., & Posner, M. I. (1967). Human performance. In *Human performance*. Brooks/Cole.
- Gao, B., Kim, B., Kim, J.-I., & Kim, H. (2019). Amphitheater Layout with Egocentric Distance-Based Item Sizing and Landmarks for Browsing in Virtual Reality. *International Journal of Human-Computer Interaction*, 35(10), 831–845. <https://doi.org/10.1080/10447318.2018.1498654>
- Gaur, V., Uddin, Md. S., & Gutwin, C. (2018). Multiplexing spatial memory: increasing the capacity of FastTap menus with multiple tabs. *Proceedings of the 20th International Conference on Human-Computer Interaction with Mobile Devices and Services - MobileHCI '18*, 1–13. <https://doi.org/10.1145/3229434.3229482>
- Grant, D. A. (1948). The latin square principle in the design and analysis of psychological experiments. *Psychological Bulletin*, 45(5), 427–442. <https://doi.org/10.1037/H0053912>
- Gutwin, C., & Cockburn, A. (2006). Improving list revision with ListMaps. *Proceedings of the Workshop on Advanced Visual Interfaces, 2006*, 396–403. <https://doi.org/10.1145/1133265.1133347>
- Gutwin, C., Cockburn, A., & Lafreniere, B. (2015). Testing the rehearsal hypothesis with two FastTap interfaces. *Proceedings of the 41st Graphics Interface Conference - GI '15*, 223–231.
- Gutwin, C., Cockburn, A., Scarr, J., Malacria, S., & Olson, S. C. (2014). Faster command selection on tablets with FastTap. *Proceedings of the ACM Conference on Human Factors in Computing Systems - CHI '14*, 2617–2626. <https://doi.org/10.1145/2556288.2557136>
- Hasher, L., & Zacks, R. T. (1979). Automatic and effortful processes in memory. *Journal of Experimental Psychology: General*, 108(3), 356–388. <https://doi.org/10.1037/0096-3445.108.3.356>
- Hick, W. E. (1952). On the rate of gain of information. *Quarterly Journal of Experimental Psychology*, 4(1), 11–26. <https://doi.org/10.1080/17470215208416600>
- Hubenschmid, S., Zagermann, J., Leicht, D., Reiterer, H., & Feuchtner, T. (2023). ARound the Smartphone: Investigating the Effects of Virtually-Extended Display Size on Spatial Memory. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–15. <https://doi.org/10.1145/3544548.3581438>
- Jannat, M. E., & Hasan, K. (2023). Exploring the Effects of Virtually-Augmented Display Sizes on Users' Spatial Memory in Smartwatches. *Proceedings - 2023 IEEE International Symposium on Mixed and Augmented Reality, ISMAR 2023*, 553–562. <https://doi.org/10.1109/ISMAR59233.2023.00070>
- Jansen, Y., Schjerlund, J., & Hornbæk, K. (2019). Effects of Locomotion and Visual Overview on Spatial Memory when Interacting with Wall Displays. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems - CHI '19*, 1–12.
- Joshi, N., & Vogel, D. (2019). An Evaluation of Touch Input at the Edge of a Table. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems - CHI '19*, 1–12.
- Kessels, R. P. C., Jaap Kappelle, L., de Haan, E. H. F., & Postma, A. (2002). Lateralization of spatial-memory

- processes: evidence on spatial span, maze learning, and memory for object locations. *Neuropsychologia*, 40(8), 1465–1473.
- Kurtenbach, G., & Buxton, W. (1994). User learning and performance with marking menus. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Celebrating Interdependence - CHI '94*, 258–264. <https://doi.org/10.1145/191666.191759>
- Lafreniere, B., Gutwin, C., Cockburn, A., & Grossman, T. (2016). Faster Command Selection on Touchscreen Watches. *Proceedings of the ACM Conference on Human Factors in Computing Systems - CHI '16*, 4663–4674. <https://doi.org/10.1145/2858036.2858166>
- Lepinski, G. J., Grossman, T., & Fitzmaurice, G. (2010). The design and evaluation of multitouch marking menus. *Proceedings of the ACM Conference on Human Factors in Computing Systems - CHI '10*, 2233–2242. <https://doi.org/10.1145/1753326.1753663>
- Mobile App Statistics Everyone Should Know in 2023*. (n.d.). Retrieved April 4, 2024, from <https://techreport.com/statistics/app-statistics/>
- Mollashahi, E. S., Sami Uddin, M., & Gutwin, C. (2018). Improving revisitation in long documents with two-level artificial-landmark scrollbars. *Proceedings of the Workshop on Advanced Visual Interfaces AVI*. <https://doi.org/10.1145/3206505.3206554>
- Parhi, P., Karlson, A. K., & Bederson, B. B. (2006). Target size study for one-handed thumb use on small touchscreen devices. *ACM International Conference Proceeding Series*, 159, 203–210. <https://doi.org/10.1145/1152215.1152260>
- Postma, A., & De Haan, E. H. F. (1996). What was where? Memory for object locations. *The Quarterly Journal of Experimental Psychology. A, Human Experimental Psychology*, 49(1), 178–199. <https://doi.org/10.1080/713755605>
- Scarr, J., Cockburn, A., Gutwin, C., Bunt, A., Cechanowicz, J. E., Scarr, J., Cockburn, A., Gutwin, C., Bunt, A., & Cechanowicz, J. E. (2014). The usability of CommandMaps in realistic tasks. *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems - CHI '14*, 2241–2250.
- Schramm, K., Gutwin, C., & Cockburn, A. (2016). Supporting Transitions to Expertise in Hidden Toolbars. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '16*, 4687–4698. <https://doi.org/10.1145/2858036.2858412>
- Siegel, A. W., & White, S. H. (1975). The Development of Spatial Representations of Large-Scale Environments. *Advances in Child Development and Behavior*, 10, 9–55. [https://doi.org/10.1016/S0065-2407\(08\)60007-5](https://doi.org/10.1016/S0065-2407(08)60007-5)
- Thorndyke, P. W., & Goldin, S. E. (1983). Spatial Learning and Reasoning Skill. In *Spatial Orientation* (pp. 195–217). Springer US. https://doi.org/10.1007/978-1-4615-9325-6_9
- Thorndyke, P. W., & Hayes-Roth, B. (1982). Differences in spatial knowledge acquired from maps and navigation. *Cognitive Psychology*, 14(4), 560–589. [https://doi.org/10.1016/0010-0285\(82\)90019-6](https://doi.org/10.1016/0010-0285(82)90019-6)
- Uddin, M. S. (2022). *Use of Landmarks to Improve Spatial Learning and Revisitation in Computer Interfaces*. University of Saskatchewan.
- Uddin, Md. S., & Gutwin, C. (2016). Rapid Command Selection on Multi-Touch Tablets with Single-Handed HandMark Menus. *Proceedings of the 2016 ACM International Conference on Interactive Surfaces and Spaces*, 205–214. <https://doi.org/10.1145/2992154.2992172>
- Uddin, Md. S., & Gutwin, C. (2021). The Image of the Interface: How People Use Landmarks to Develop Spatial Memory of Commands in Graphical Interfaces. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1–17. <https://doi.org/10.1145/3411764.3445050>
- Uddin, Md. S., Gutwin, C., & Lafreniere, B. (2016). HandMark Menus: Rapid Command Selection and Large Command Sets on Multi-Touch Displays. *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 5836–5848. <https://doi.org/10.1145/2858036.2858211>
- Zhai, S., & Kristensson, P.-O. (2003). Shorthand writing on stylus keyboard. *Proceedings of the Conference on Human Factors in Computing Systems - CHI '03*, 97–104. <https://doi.org/10.1145/642611.642630>
- Zheng, J., Bi, X., Li, K., Li, Y., & Zhai, S. (2018). M3 Gesture Menu: Design and Experimental Analyses of Marking Menus for Touchscreen Mobile Interaction. *Proceedings of the Conference on Human Factors in Computing Systems - CHI '18*, 1–14. <https://doi.org/10.1145/3173574.3173823>
- Zheng, J., Lewis, B., Avery, J., & Vogel, D. (2018). FingerArc and FingerChord: Supporting Novice to Expert Transitions with Guided Finger-Aware Shortcuts. *The 31st Annual ACM Symposium on User Interface Software and Technology - UIST '18*, 347–363. <https://doi.org/10.1145/3242587.3242589>