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Using a Blocklist to Improve the Security of User Selection of Android Patterns

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Mobile Authentication

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• Access to smartphones can be secured in the following ways:



	Fingerprint	4-digit PIN	Pattern	6-digit PIN	Face	Password	
	57%	46%	27%	16%	12%	4%	
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How Secure are Patterns?

 Despite 389,112 options, most users choose common, easily guessable patterns.





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Study Objective

- Interested in the security and usability impact of blocking common patterns.
- We ask two questions:
 - What is the security and usability impact of blocklists on patterns?
 - What is the right-sized blocklist that balances security and usability of patterns?







Study Design

- Online study on Amazon Mturk (n = 1006).
- Participants selected patterns under 6 treatments:
 - Control: No blocklist intervention.
 - BL-32: 12 patterns blocked.
 - BL-16: 54 patterns blocked.
 - BL-8: 105 patterns blocked.
 - BL-4: 172 patterns blocked.
 - BL-2: 581 patterns blocked.
- Each participant was assigned to one treatment.







Primary Findings

- Blocklists, even small ones, improve the security of selected patterns.
- Blocklists prime users to consider security when selecting patterns.
- Blocklists do not significantly impact the usability of patterns.
- A blocklist size of 100 would well balance security and usability.



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Security Analysis: Threat Models

Perfect Knowledge Attacker

 Has complete knowledge of the frequency order of patterns, from the most to the least frequent.

Simulated Attacker

 Knows a subset of the patterns and constructs a model based on that observed distribution.



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Security Analysis: Perfect Knowledge Guessing

	Throttled Attack (%)			Unthrottled Attack (Bits)			
Treatment	λ3	λ_{10}	λ_{30}	H_{∞}	$\widetilde{G}_{0.1}$	$\widetilde{G}_{0.3}$	$\widetilde{G}_{0.5}$
Control	13.1 %	22.9 %	41.1 %	3.75	4.66	6.00	6.93
BL-32	9.0%	18.0%	33.1 %	5.01	5.82	6.65	7.26
BL-16	7.3 %	15.6%	29.9%	5.33	6.04	7.00	7.45
BL-8	8.0 %	17.1 %	31.9%	5.33	5.89	6.81	7.33
BL-4	4.6 %	10.9 %	22.3 %	6.33	6.64	7.34	7.61
BL-2	5.1 %	13.1 %	27.9%	5.75	6.31	7.00	7.43

Note: A perfect knowledge attacker has complete knowledge of the frequency order of the patterns, from the most frequent to the least frequent.



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Security Analysis: Simulated Guessing



Note: A simulated guesser knows a subset of the patterns and constructs a model based on that distribution. We used a Markov Model to break ties.



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Changes in Pattern Selection Strategies



Participants move from simple to complex pattern selection strategies after encountering blocklists.



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Usability

	Control	BL_32	BL_16	BL_8	BL_4	BL_2
Mean Selection Time	13.64s	13.41s	16.67s	19.27s	25.52s	34.24s
Median	7.38s	9.12s	12.34s	13.88s	17.48s	26.70s
Standard Deviation	26.91s	12.17s	15.98s	17.04s	25.25s	29.23s
Mean Entry Time	1.53s	1.46s	1.53s	1.73s	1.87s	1.79s
Median	1.27s	1.19s	1.33s	1.46s	1.53s	1.62s
Standard Deviation	1.10s	0.94s	0.83s	1.00s	1.35s	0.91s
Mean Recall Attempts	1.33	1.35	1.27	1.35	1.52	1.52
Median	1.00	1.00	1.00	1.00	1.00	1.00
Standard Deviation	0.87	0.82	0.64	0.78	1.03	1.03
Recall Success Rate	100.00%	99.55%	100.00%	99.54%	100.00%	99.62%
Mean SUS Score	78.64	78.77	78.01	76.96	76.47	71.62
Median	82.5	80.0	80.0	80.0	77.5	75.0
Standard Deviation	17.37	16.51	16.47	16.84	16.80	17.82

Selection time increases due to interaction with blocklists; entry time and recall rates are unaffected.



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Conclusion

- We studied the security and usability impact of blocklists on Android patterns.
- We find that even small blocklists improve security while minimally impacting usability.
- Our results indicate that blocking 100 most common patterns would well balance security and usability of patterns.







Thank you! Ping us!

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