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Cognitive Impact Of Multiple Gestures In Simultaneous Tasks

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Abstract
This study examines the cognitive impact of mid-air hand gestures (hover, pinch, and swipe) in multitasking environments, evaluating their efficiency, mental load, and effects across age groups. A laboratory-based experimental design was conducted with 120 participants (aged 18–65), who engaged in tasks of varying complexity (low/high) and received one of three feedback modalities (visual, auditory, haptic). Objective (reaction time, error rate, EEG activity) and subjective (NASA-TLX) metrics were collected. Findings indicate that the hover gesture achieved the best balance between speed and cognitive load (1,200 ms; NASA-TLX: 45/100), making it suitable for high-demand contexts such as robotic surgery or air traffic control. Conversely, the swipe gesture increased mental load by 65% in complex tasks. Haptic feedback emerged as the most effective, reducing cognitive load by 34% (EEG theta: 4.3 µV vs. 6.5 µV visual) and improving accuracy to 92%. Significant age-related differences were also observed: older adults exhibited 40% slower response times; however, haptic feedback partially mitigated this performance gap. These results highlight the need for inclusive, adaptive interfaces grounded in cognitive ergonomics. The study concludes that hover gestures combined with haptic feedback provide an optimal configuration for cognitively demanding environments. This research offers a rigorous methodological framework and practical design recommendations for implementing gesture-based interaction in medical, industrial, and extended reality applications.
Keywords: *cognitive load, haptic feedback, gesture interaction, age inclusivity, adaptive interfaces*.

INTRODUCTION

In recent decades, the evolution of user interfaces has undergone a significant transformation with the incorporation of natural interaction technologies, among which manual gestures in the air stand out. This modality, which dispenses with physical contact with surfaces, has proven to be particularly valuable in contexts where hygiene, precision and speed are imperative, such as in surgical settings, clinical laboratories, industrial control centres or extended reality applications (Erazo et al., 2019). As these technologies gain a foothold in critical and demanding systems, an essential question emerges from the perspective of cognitive ergonomics: how does the simultaneous use of multiple gestures affect the user's mental load, especially when performing parallel tasks that demand divided attention?
Gesture interaction in the air has been promoted as a more intuitive and fluid way to communicate with digital systems, by eliminating dependence on intermediate physical devices. However, its implementation in scenarios of high cognitive demand poses challenges that have not yet been completely resolved, related to the motor complexity of gestures, ambiguity in their interpretation, system latency and, particularly, the lack of natural tactile feedback. These elements can increase the user's cognitive load, interfering with performance in primary tasks or generating errors that compromise the security or effectiveness of the system (Sun et al., 2020; Pfeiffer et al., 2020).

Cognitive load, understood from Mayer's (2003) theory of multimedia learning, represents the amount of mental resources required by a person to process, retain and act on certain information. In environments where users must perform multiple actions simultaneously, for example, monitoring alerts while selecting elements using gestures, an increase in cognitive load can have negative consequences, such as errors, mental fatigue or decreased response speed. Recent studies have shown that even gestures considered intuitive, such as the "hover", can become sources of cognitive interference when combined with visuospatial tasks or more complex mental operations (Mao et al., 2024; Theil, 2019).

The literature on gestural interaction has reported divergent findings regarding the impact of these systems on cognitive efficiency. On the one hand, research such as that of Vogiatzidakis and Koutsabasis (2018) suggests that hand-held gestures in the air can facilitate interaction by offering a more natural experience, especially when movements are simple and consistent. These authors highlight that the absence of physical devices favors the fluidity of communication with the machine, which could translate into a lower mental load compared to traditional systems. However, other research, such as that of Theil (2019), shows that gestures that involve greater motor complexity, semantic ambiguity, or sequential memory requirements tend to significantly increase cognitive load, negatively affecting user performance in multitasking situations.

A fundamental aspect in the evaluation of gestural interaction is the nature of the secondary task with which it is combined. In this sense, Chaker (2025) has pointed out that visuospatial tasks, those that require the integration of visual stimuli with precise motor responses, are particularly vulnerable to interference when a second gesture-based task is introduced. For example, in aviation, pilots must keep an eye on multiple instruments while operating digital controls, which can be compromised if the system requires complex or ambiguous gestures. Similarly, in medical contexts, studies such as those by van Amsterdam et al. (2021) report that surgeons have higher error rates when using gestures to confirm selections during laparoscopic procedures, compared to traditional methods such as physical buttons or touch screens.

Another critical component in gestural interaction is the quality and modality of the feedback provided by the system. Feedback plays a fundamental role in the user's self-regulation, allowing them to confirm if their action was correctly interpreted by the system. Research such as that of Kaaresoja and Brewster (2010) has shown that the lack of immediate and clear feedback forces the user to dedicate additional cognitive resources to validate their interaction, which can increase mental effort and reduce overall efficiency. In this sense, studies on tactile interfaces have shown that haptic feedback that uses vibrations or tactile stimuli can significantly reduce cognitive load (Zhou et al., 2007). However, most airborne gestural systems lack this feedback modality, relying solely on visual or auditory cues, whose effectiveness in multitasking scenarios has been little explored (Oh et al., 2015; Alvarez-Santos et al., 2014).

The inclusion of multimodal feedback, which combines visual, auditory and haptic feedback, has been proposed as a strategy to improve cognitive efficiency in interactive systems. Oh et al. (2015) argue that the integration of multiple sensory channels can facilitate understanding of the state of the system and reduce user uncertainty, especially in contexts where a single modality may not be sufficient. In particular, haptic feedback is presented as a promising alternative to compensate for the lack of physical contact in aerial gestures, by offering a tangible sensation that validates the execution of the command. Despite this, its implementation is still limited, and few studies have evaluated its comparative impact compared to other modalities in settings of high cognitive demand.

The diversity of users is another relevant axis in the design of gestural systems, especially with regard to age, technological experience and motor skills. Research such as that by Özer and Göksun (2020) emphasizes that these variables significantly influence the way users perceive and execute gestures, as well as their ability to manage simultaneous tasks. For example, older adults tend to have greater difficulty coordinating precise movements while maintaining attention on a complex cognitive task, which can lead to greater mental load and decreased overall performance (Arslan & Göksun, 2022). This phenomenon poses important challenges for the development of inclusive interfaces, especially in applications where the user population is heterogeneous, such as in public transport systems, medical services or virtual education.

Vasylkiv (2020) has explored intergenerational differences in gestural interaction, identifying patterns that suggest the need to adapt systems to the specific capacities of each age group. In this context, the implementation of adaptive interfaces capable of dynamically adjusting the level of complexity of gestures, the feedback modality or the sensitivity of the system represents a promising way to improve overall usability and ensure technological access equity. However, these strategies require a deep understanding of individual differences and how these manifest themselves in interaction with emerging technologies.

The present study aims to address these problems through a rigorous methodological approach that combines quantitative and qualitative techniques to analyze the cognitive impact of the use of multiple gestures in multitasking environments. Based on theoretical frameworks from cognitive psychology, human-computer interaction and ergonomics, an experimental design is proposed that considers critical variables such as the type of gesture, the complexity of the secondary task, the feedback modality and the age of the user. Through the objective measurement of brain activity (EEG), operational performance (response time, error rate) and perceived subjective load (NASA-TLX), this work seeks to generate empirical evidence that allows optimizing the design of gestural interfaces for real applications.

In particular, it is expected to identify which combinations of gestures and feedback are most efficient in terms of cognitive load, and how these interact with individual user characteristics. Thus, it is intended not only to advance in the theoretical understanding of gestural interaction in complex contexts, but also to offer practical recommendations for the development of more intuitive, robust and inclusive systems. These recommendations could benefit multiple sectors, including robot-assisted medicine, aerospace, augmented reality, virtual education, and other domains where contactless interaction is becoming increasingly relevant.

In short, this research seeks to provide a comprehensive vision of the phenomenon, integrating experimental results with interdisciplinary reflections, to consolidate a conceptual and methodological framework that guides the design of future generations of user-centered gestural interfaces. Through this approach, the aim is to close existing gaps in the literature, respond to technical and cognitive challenges that have not yet been resolved, and promote more efficient, safe, and accessible interaction for all user profiles.

METHODOLOGY

The present study adopted a mixed methodological approach that integrated quantitative and qualitative techniques with the aim of comprehensively evaluating the cognitive impact derived from the use of multiple gestures in multitasking environments. This strategy made it possible to capture both objective performance indicators and subjective perceptions of the participants, in line with previous studies on gestural interaction in complex contexts (Erazo et al., 2019). The experimental design was developed in controlled laboratory conditions that replicated scenarios of high cognitive demand, such as operating rooms, cockpits, or automated industrial environments, following protocols established in previous research (van Amsterdam et al., 2021).

The sample consisted of 120 participants, selected through a stratified sampling by age, in order to ensure diversity in terms of motor skills, levels of technological experience and cognitive abilities. An equal distribution was established between genders (60 women and 60 men), with ages ranging from 18 to 65 years. For the subsequent analysis, the participants were organized into three age groups (18-30, 31-50, and 51-65 years), following methodological criteria based on research on intergenerational cognitive variability (Özer & Göksun, 2020; Arslan & Göksun, 2022). This stratification allowed us to explore the effect of age on cognitive performance, a factor that has been shown to significantly influence gestural interaction.

The experiment relied on high-precision motion tracking technologies, specifically Kinect v2 and Leap Motion sensors, pre-calibrated to ensure a capture accuracy of at least 0.5mm. These devices have been widely validated in non-contact interaction studies and were selected for their threedimensional sensing capability and compatibility with 2D and 3D visualization environments (Vogiatzidakis & Koutsabasis, 2018). The tasks were presented through two platforms: a 32-inch touchscreen and an Oculus Quest 2 virtual reality headset, which made it possible to compare cognitive behavior in traditional and immersive viewing contexts.

To measure cognitive load, a set of complementary metrics was used. First, an Emotiv EPOC+ EEG sensor was used, which recorded brain activity in real time, with special emphasis on the theta (4–7 Hz) and alpha (8–13 Hz) frequency bands, associated with mental effort and attentional processes according to the neuroergonomic literature (Sun et al., 2020). In parallel, the NASA-TLX scale was applied, an instrument validated in various contexts of human-computer interaction, which measures subjective perception of load in dimensions such as effort, frustration, performance, and mental demand (Chaker, 2025).

Operational performance metrics included response time (in milliseconds), error rate (percentage of incorrect executions), and efficiency in task completion. These indicators were automatically captured using LabVIEW-based analysis software, which ensured accuracy in the collection and synchronization of physiological and behavioral data. Each participant completed twelve experimental sessions organized using a 3×2 factorial design, where the independent factors were the type of gesture and the level of complexity of the secondary task. The selected hover, pinch, and swipe gestures were based on their frequency of use and validation in previous research (Erazo et al., 2019; Mao et al., 2024; Theil, 2019). Secondary tasks ranged from a low-complexity condition (passive monitoring of visual alerts) to a high-complexity condition (solving arithmetic problems while executing the gesture).

The order of presentation of the conditions was completely randomized for each participant in order to mitigate learning effects or accumulated fatigue. In addition, a five-minute break was included between each session, thus allowing cognitive recovery and reducing possible biases derived from fatigue. Prior to the start of the formal experiment, participants completed a 15-minute standardized training phase, where they became familiar with gestures, interfaces, and feedback modalities, in an environment guided by the research staff.

In relation to the feedback of the system, three experimental conditions were implemented. The first consisted exclusively of visual cues, represented by confirmatory icons on screen. The second included more auditory visual feedback, through brief tones associated with the execution of gestures, following the protocol proposed by Oh et al. (2015). Finally, the third condition combined visual and haptic feedback, the latter provided by a vibrating vest (TactSuit X40), which generated a localized physical response in the participant's torso upon successful completion of a gesture. This configuration made it possible to compare the differential effect of each feedback modality on cognitive load and performance, in agreement with studies on multimodal feedback in gestural interaction (Kaaresoja & Brewster, 2010; Zhou et al., 2007).

The analysis of the quantitative data was carried out using the SPSS v27 and R programs, applying statistical models appropriate to the characteristics of the design. Repeated measures analyses of variance (ANOVA) were carried out in order to identify significant differences between conditions in the indicators of cognitive load (EEG and NASA-TLX) and performance. Additionally, Pearson's correlation analysis was applied to explore relationships between age, technological experience, and performance. Finally, multiple linear regression models were built to identify significant predictors of efficiency, considering variables such as gestural accuracy, feedback latency, and level of task complexity.

The qualitative data, obtained through semi-structured interviews at the end of the experimental sessions, were analyzed through thematic coding with the NVivo 12 software. The analysis structure was based on the conceptual framework proposed by Alvarez-Santos et al. (2014), allowing to categorize perceptions of usability, system clarity, comfort, and perception of mental load.

Overall, this methodology seeks to offer a comprehensive view of the phenomenon, incorporating advanced technological tools and interdisciplinary theoretical frameworks. The proposed experimental design not only allows to rigorously evaluate the impact of multiple gestures in multitasking conditions, but also to generate knowledge applicable to the design of adaptive and cognitively efficient gestural interfaces in critical domains such as medicine, industry and extended reality.

RESULTS

Performance by gesture type and task complexity

To evaluate the effect of the type of gesture on cognitive performance under multitasking conditions, the performance of participants in visual selection tasks with two levels of complexity (low and high) was analyzed, using three types of gestures previously validated in the literature: hover, pinch, and swipe (Erazo et al., 2019; Mao et al., 2024; Theil, 2019). Measures of response time (ms), error rate (% of incorrect executions), and subjective cognitive load were recorded using the NASA-TLX questionnaire, normalized to a scale of 0–100.

The results are summarized in the following table:

Table 1. Performance by gesture type and task complexity

Gesture	Low Task (Time/ms)	High Task (Time/ms)	Error Rate (%)	Cognitive Load (NASA-TLX)
Hover	1,200 ± 150	1,800 ± 200	5.2 ± 1.1	45 ± 8
Pinch	1,050 ± 120	2,100 ± 180	8.7 ± 1.5	58 ± 7
Swipe	1,400 ± 160	2,500 ± 220	12.3 ± 2.0	65 ± 9

A repeated measures analysis of variance (ANOVA) was applied which revealed statistically significant differences in response time between gesture types ($F(2, 237) = 28.6$, $p < 0.001$, $\eta^2 = 0.19$). The interaction between type of gesture and task complexity was also significant ($F(2, 237) = 12.4$, $p < 0.001$), indicating that the hover gesture maintained a more stable performance in the face of increased cognitive demand, compared to pinch and swipe. In addition, a strong positive correlation was observed between NASA-TLX scores and theta activity in EEG ($r = 0.72$, $p < 0.01$), which validates their joint use as indicators of mental load (Chaker, 2025).

From a theoretical perspective, these results support the findings of Erazo et al. (2019), who identified the hover gesture as particularly robust in confirmation tasks. Although previous studies such as those by Vogiatzidakis and Koutsabasis (2018) suggested that pinch could be perceived as more natural, our results show that its motor execution increases cognitive load in multitasking scenarios. This finding coincides with what Theil (2019) proposes, who warns about the complexity of compound gestures in older users or in conditions of high attentional pressure.

Effect of Multimodal Feedback

Impact of feedback type in highly complex environments

In order to analyze how different feedback modalities influence cognitive load and accuracy in demanding tasks, three experimental conditions were compared: visual feedback only, visual plus auditory, and visual plus haptic. Participants completed highly complex tasks with the hover gesture, previously selected for its superior performance. Execution time (ms), accuracy (% of correct answers) and objective cognitive load were evaluated using spectral power in the theta band of the EEG.

Table 2. Impact of feedback on cognitive load and performance

Feedback	Time (ms)	Accuracy (%)	Cognitive Load (EEG Theta)
Visual	2,000 ± 250	78 ± 6	6.5 µV ± 1.2
Visual + Auditory	1,750 ± 200	85 ± 5	5.8 µV ± 1.0
Visual + Haptic	1,600 ± 180	92 ± 4	4.3 µV ± 0.8

The ANOVA analysis showed significant differences between feedback conditions for all variables assessed ($F(2, 237) = 34.2$, $p < 0.001$). Post-hoc analysis with Tukey HSD indicated that haptic feedback reduced cognitive load by 34% compared to visual condition, with an 18% improvement in accuracy ($p < 0.001$). Theta power, as a marker of cognitive effort, was significantly lower under the haptic condition compared to the auditory and visual condition ($p < 0.01$), confirming a lower mental load.

These findings expand on the work of Kaaresoja and Brewster (2010), who reported that feedback latency and modality directly influence cognitive efficiency. Although Oh et al. (2015) had highlighted the potential of auditory feedback to reinforce gesture learning, our data indicate that, in high-demand contexts, haptic feedback provides a significant advantage by offering immediate and tangible sensory confirmation. This effect is also consistent with the results of Zhou et al. (2007), who demonstrated in surgical settings that haptic feedback improves the perception of control and reduces operational errors.

Effect of age on the execution of gestures with haptic feedback

In order to explore how the user's age modulates the cognitive impact of gestures in multitasking, the performance of the three defined age groups (18–30, 31–50 and 51–65 years) was analyzed under the same condition: use of the hover gesture with visual and haptic feedback, in highly complex tasks. Response time (ms), error rate (%) and subjective perception of cognitive load were measured using NASA-TLX.

Table 3. Performance and cognitive load by age group

Age	Time (ms)	Errors (%)	NASA-TLX
18-30	1,500 ± 150	4.1 ± 0.9	40 ± 6
31-50	1,700 ± 170	6.3 ± 1.2	52 ± 7
51-65	2,100 ± 200	9.8 ± 1.8	63 ± 8

Multiple linear regression analysis showed that age significantly predicts both response time ($\beta = 0.42$, $p < 0.001$) and perceived cognitive load ($\beta = 0.38$, $p < 0.01$). In addition, an increase in frontal alpha activity was observed in the group of older adults, which has been interpreted as a cognitive compensation mechanism (Arslan & Göksun, 2022).

These results are consistent with previous studies by Özer and Göksun (2020), who pointed out that age and technological experience condition the efficiency in the execution of gestures. However, the present research provides evidence that the implementation of haptic feedback can partially attenuate these performance gaps, reducing errors and facilitating adaptation for older users. This observation suggests that inclusive design principles, based on adaptive and multimodal interfaces, may be key to ensuring technological accessibility and equity, as proposed by Vasylkiv (2020) and Vinot et al. (2016).

DISCUSSION

The findings of this study provide solid evidence on the differential impact that manual gestures in the air exert on cognitive load in multitasking contexts, incorporating objective, subjective and behavioral measurements. From a robust experimental design, it was identified that the hover gesture offers consistently superior performance compared to other more complex gestures such as pinch and swipe, particularly in high-demand tasks. These results not only reinforce previous research that highlights the efficiency of the hover gesture to confirm selections (Erazo et al., 2019), but also expands on this evidence by testing its efficacy under conditions of high cognitive load.

Factor analysis allowed us to observe how the interaction between type of gesture and task complexity significantly influences performance. Unlike gestures such as pinch – which, although fast on simple tasks, generated a noticeable cognitive overload on complex tasks – the hover gesture showed greater stability, suggesting a more accessible learning curve and less motor interference. This finding partially contradicts the claims of Vogiatzidakis and Koutsabasis (2018), who argued that gestures such as pinching could be more natural for users. In our study, the motor nature of the pinch gesture, requiring greater fine coordination and muscle activation, seemed to hinder its efficient execution when integrated with parallel cognitive tasks, a result consistent with what Theil (2019) proposed.

Another relevant contribution of the study was the comparison between different feedback modalities. Haptic feedback was positioned as the most effective, significantly reducing both perceived mental effort and cortical activation in theta bands, while improving execution accuracy. This evidence supports the hypothesis that contactless interaction systems benefit markedly from the incorporation of tactile feedback, compensating for the absence of direct physical contact with the interface. This result is in line with the studies of Kaaresoja and Brewster (2010), who indicated that the latency and clarity of feedback directly affect the user's cognitive load. It also reinforces what was proposed by Zhou et al. (2007) in surgical contexts, where haptic feedback not only improves safety, but also operational efficiency.

Although auditory feedback also showed improvements over the purely visual condition, its effect was significantly less than that of haptics. This difference can be explained by the fact that auditory signals, depending on the acoustic context and the user's selective attention, present greater variability in their interpretation. As noted by Oh et al. (2015), the effectiveness of auditory feedback may be limited in environments where ambient noise or multitasking make it difficult to process.

From a usability and inclusion perspective, one of the most significant findings was the identification of age differences in cognitive performance. Older adults (51–65 years) showed longer response times and greater perceived load, which is consistent with research such as that of Arslan and Göksun (2022), which report a decrease in the ability to coordinate motor and cognitive tasks simultaneously in the elderly population. However, the fact that haptic feedback has partially mitigated these gaps is of great relevance, as it suggests that the design of adaptive interfaces can favor a more equitable interaction experience between users of different ages. This aspect, scarcely addressed in previous literature (Vasylkiv, 2020), opens up new lines of research in the inclusive design of emerging technologies.

The data obtained also validate the integration of physiological tools (EEG) with subjective scales such as NASA-TLX, a strategy recommended by Chaker (2025) to achieve a more complete and objective assessment of cognitive load. The strong correlation observed between theta potency and subjective scores not only reinforces the validity of the methodological approach, but also suggests that the combination of both metrics may be key for future real-time evaluations of gestural systems in real operating environments.

From the applied point of view, these results provide concrete guidelines for the design of interactive systems based on gestures in air. First, it is advisable to prioritize simple gestures such as hover in scenarios where accuracy, speed of response, and mental load are critical factors, such as robotic surgery, aviation, industrial control, or professional virtual reality. Second, haptic feedback, preferably localized and with minimal latency, should be integrated to reduce mental load and increase the perception of control. Finally, it is suggested to implement adaptive mechanisms that allow customizing the level of complexity of the gesture and the feedback modality according to the characteristics of the user, such as age or technological experience.

However, this study also has limitations that should be considered. First, the experimental conditions, although carefully designed, were developed in a controlled environment that might not fully reflect the dynamics of real environments such as operating rooms, cockpits, or industrial scenarios. Second, the sample, although diverse in age, was limited to users with normal vision and mobility, which restricts generalization to populations with sensory or motor disabilities. In addition, the use of only three gestures and three types of feedback represents a simplification of the real range of possibilities in commercial systems. Future studies should explore a greater variety of gestural combinations, contextual conditions, and user profiles, as well as apply longitudinal methodologies to assess learning and retention in the use of gestures.

Taken together, the findings of this study not only expand the theoretical understanding about gestural interaction in multitasking contexts, but also offer valuable practical implications for the design of adaptive, cognitively efficient, and inclusive interfaces. By articulating empirical evidence with solid theoretical foundations, this research contributes to the advancement of the field of human-computer interaction and lays the foundation for the development of new user-centered technologies.

CONCLUSIONS

This study provides robust empirical evidence on the cognitive impact of hand-in-air gestures in multitasking contexts, highlighting the critical role of gestural simplicity, feedback modality, and individual differences between users. Through a controlled experimental design and a multidisciplinary approach, it was possible to identify performance patterns that allow guiding the design of more efficient, accessible and inclusive gestural interfaces.

Among the main findings, it stands out that the hover gesture offers an optimal balance between execution speed, low error rate and lower cognitive load, especially in complex tasks. This consistency positions it as a preferential option over more complex gestures such as pinch or swipe, whose motor demand increases the mental load in high-demand scenarios. In addition, it was evidenced that haptic feedback not only improves accuracy, but also significantly reduces cognitive load, validating its incorporation as an essential component in contactless interaction systems.

Likewise, significant differences associated with age were identified, where older adults experienced longer response times and perceived load. However, the use of haptic feedback demonstrated a moderating capacity, partially attenuating these gaps, which reinforces the need to develop adaptive interfaces based on user profiles. This inclusive perspective is especially relevant in sectors such as health, transport or industry, where the diversity of users is an operational factor.

The present work also validates the efficacy of combining objective metrics (EEG) with subjective measures (NASA-TLX) for a more comprehensive assessment of cognitive load. The high correlation observed between the two strengthens the relevance of this methodological approach for interaction studies in real environments.

Based on these findings, the following practical recommendations are proposed: prioritize simple gestures such as hover in critical applications; integrate haptic feedback to improve accuracy and reduce mental effort; and designing adaptive systems that consider variables such as age, experience, and context of use. While this study was conducted in a controlled environment, its results lay a solid foundation for future research in real-world settings, extending its applicability to fields such as robotic surgery, aviation, extended reality, and industrial automation.

In short, this research contributes to the development of user-centred technologies and offers a methodological and conceptual framework to optimise gestural interaction in systems with high cognitive demand.

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