The operational time window for quantum reservoir computing beyond the edge of chaos

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Abstract: Quantum reservoir computing harnesses complex quantum dynamics to process temporal data; however, the selection of its hyperparameters, such as the system's evolution time, is often heuristic and lacks a physical justification. This work investigates quantum chaotic behaviour as a criterion for selecting this evolution time, using a transverse-field Ising model as a reservoir. We find that, while performance peaks at the so-called edge of chaos in terms of magnetic field strength, the optimal evolution time lies within a functional window bounded by two distinct timescales: a newly introduced lower bound set by the temporal collapse of observable variances and an upper bound given by the Thouless time. Notably, the optimal time is consistently shorter than the Thouless time, establishing it as an upper bound rather than a direct target, contrary to what has been suggested in previous studies. Furthermore, introducing measurement back-action shifts this optimal regime, challenging the notion of a universal edge of chaos rule. Our results demonstrate that effective quantum reservoir computing requires a nuanced balance between chaos, evolution time, and measurement strength, with fully chaotic systems proving detrimental for memory tasks.
Keywords: Quantum machine learning, quantum reservoir computing, quantum information, quantum chaos, information scrambling, exponential concentration.
SDGs: Industry, Innovation, and Infrastructure (SDG9).

I. Introduction

Quantum reservoir computing (QRC) is a quantum machine learning framework for time-series analysis. It exploits the dynamics of a quantum system, called the reservoir, to process input signals [1]. Importantly, the training phase focuses solely on optimising a linear combination of measured observables (via, for instance, linear regression). This promising approach has been explored both numerically [2] and experimentally [3].

The algorithm processes a time series through three recurrent steps applied to each element. First, the input is injected by encoding the k-th element of the time series into the state of one or more input qubits, according to the chosen scheme. Next, the reservoir evolves under its natural dynamics. Finally, information is extracted via readout, where a set of observables is measured, either projectively (resetting the system) or weakly (allowing continuous evolution) [4, 5]. These measured observables are then mapped to the final prediction via a trained linear readout layer. This linearity makes QRC promising for avoiding barren plateaus and local minima, highly-discussed issues in variational quantum algorithms [6]. The required nonlinearity is typically introduced through the encoding step, independent of system's dynamics [7].

The selection of the evolution time Δt for optimal QRC performance is typically treated as a heuristic hyperparameter optimisation. While various timescales characterise quantum dynamics, no single one fully captures the complex behaviour of QRC systems. This work focuses on the timescale associated with the scrambling dynamics of quantum chaotic systems.

Previous studies [8] have investigated the underlying timescales of many-body quantum chaotic systems, governed by a characteristic temporal boundary called the Thouless time (t_{Th}). This time marks the point after which a system's dynamics are well-described by Random Matrix Theory (RMT), such that spectral correlations become indistinguishable from those of random matrices and independent of the Hamiltonian's microscopic details. It is one of two key timescales that govern the spectral form factor (SFF) of chaotic systems. The numerical results of [8] show that QRC performance, with the Sachdev–Ye–Kitaev reservoir, can be maximised just before the Thouless time (t_{Th}). This peak in performance is considered a manifestation of the "temporal edge of many-body quantum chaos" [9]. Beyond t_{Th}, performance often plateaus at the level of a Haar-random reservoir. Haar-random systems are effective scramblers, rapidly driving the system towards a maximally mixed state and leading to poor memory capacity as information becomes delocalized into the internal correlations of a many-body system and is irretrievable via local measurements [10]. This process is formally known as quantum information scrambling.

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A known challenge in quantum chaotic systems is exponential concentration, where the expectation values of observables concentrate around a common value across different quantum states as the system size grows. This occurs when observables do not align with the system's inherent symmetries in an exponentially large Hilbert space. Consequently, an exponentially large number of measurements is necessary to resolve these values, rendering the system inefficient for computation [11, 12].

In contrast, our simulations reveal a temporal suppression of fluctuations, which we term temporal variance collapse. Here, the time-dependent variance of observables over the QRC trajectory drops near zero at specific evolution times Δt, causing the observable to freeze around a nearly constant value throughout the processing of a time series. Unlike exponential concentration, temporal variance collapse occurs when open system dynamics drive the system toward a steady state in which observables exhibit minimal temporal fluctuations. We propose the time before the variance collapses (drops to zero) in at least two measurement bases as a practical lower bound on useful Δt, since observables with near-zero variance offer less discriminative power for training.

This work has three main objectives: (1) to test the applicability of the Thouless time as a physically motivated criterion for selecting Δt in a transverse-field Ising model reservoir (TFIM); (2) to introduce and evaluate temporal variance collapse as a complementary, empirically observed lower bound for Δt; and (3) to examine how measurement back-action alters the relationship between chaos and performance. To this end, Section II details our numerical methods, including the reservoir Hamiltonian, the QRC algorithm with projective and weak measurement protocols, and the short-term memory task. Section III presents our findings, first characterising the chaotic phase transition in the TFIM, followed by an analysis of QRC performance within the operational window defined by temporal variance collapse and the Thouless time, across different measurement strengths. Finally, Section IV synthesises the results, discussing their implications for the "edge of chaos" hypothesis and for practical hyperparameter selection.

II. Methods

A. Reservoir Hamiltonian

We employ a quantum reservoir of N all-to-all connected qubits governed by the TFIM Hamiltonian:

$$\hat{H} = \sum_{i<j=1}^{N} J_{ij}\hat{\sigma}_i^x\hat{\sigma}_j^x + \frac{h}{2}\sum_{i=1}^{N}\hat{\sigma}_i^z. \tag{1}$$

Here and throughout, we work in units where $\hbar = 1$. For numerical simulations, we set $N = 6$, J_{ij} is uniformly sampled from $[-J/2, J/2]$ with $J = 1$, and the system is initialised in the state $|\psi\rangle = |0\rangle^{\otimes N}$. All Hamiltonian parameters are expressed in units of J; accordingly, the evolution time represents the product $J\Delta t$ but since $J = 1$, we simply denote it as Δt. Every simulation is averaged over 25 Hamiltonian realisations.

B. Algorithm Pipeline

The reservoir processes a time series s_k through a recurrent cycle. At each step k, the composite operation of input encoding followed by unitary evolution constitutes a completely positive trace-preserving (CPTP) map $\mathcal{L}_k$. First, the input $s_k \in [0, 1]$ is encoded by resetting the first qubit (subsystem 1) to $|\psi_k\rangle = \sqrt{1 - s_k}\,|0\rangle + \sqrt{s_k}\,|1\rangle$, while the rest of the reservoir remains in the state $\tilde{\rho}_{k-1} = \mathrm{Tr}_1(\hat{\rho}_{k-1})$. The system then evolves under $\hat{U} = e^{-i\hat{H}\Delta t}$. The full CPTP map is therefore [2, 4, 7, 13]:

$$\mathcal{L}_k(\hat{\rho}_{k-1}) = \hat{U}(|\psi_k\rangle\langle\psi_k| \otimes \mathrm{Tr}_1(\hat{\rho}_{k-1}))\hat{U}^\dagger = \hat{\rho}_k. \tag{2}$$

Following this, a set of observables is measured to form the output. In principle, exponential concentration, which becomes relevant when scaling the system size, can be mitigated by choosing observables aligned with the system's symmetries [11]. For the TFIM, $\hat{\sigma}_i^z$ and $\hat{\sigma}_i^z\hat{\sigma}_j^z$ commute with the global $\mathbb{Z}_2$ symmetry. However, since our study fixes $N = 6$ and focuses instead on temporal variance collapse, we measure a diverse set of observables, including $\hat{\sigma}_i^x$, $\hat{\sigma}_i^y$ and their correlators, to obtain a rich feature set that reflects different aspects of the reservoir's dynamics, enabling the detection of temporal freezing across multiple measurement bases, despite their potential for partial concentration. We consider two measurement protocols in QRC: the restarting protocol and the online protocol [4]. In the restarting protocol, the system is projectively measured and reinitialised for every input injection. Alternatively, an online protocol with weak measurements incorporates measurement back-action at every time step without restarting afterwards: after readout at step $k-1$, the state is modified by the element-wise application of the operator $\hat{M} = (\hat{I} + e^{-g^2/2}\hat{\sigma}^x)^{\otimes N}$ [5], yielding $\hat{\rho}_k = \hat{M} \odot \mathcal{L}_k(\hat{\rho}_{k-1})$ [5]. With $g = 0$, no measurement occurs, and the system evolves unitarily without back-action. Finite $g > 0$ introduces weak measurement with corresponding back-action, while large g approaches the projective limit within the online framework.

C. Short-term memory task

This work evaluates QRC performance on the short-term memory (STM) task, which accounts for the efficiency of the reservoir in storing past information. Concretely, the target function at each step is $y_k = s_{k-\eta}$, where $\vec{s}$ is the original time series and η is the time delay. For numerical simulations, we use a dataset of 1000 uniformly sampled random points in $[0, 1]$ and η is varied between 1 and 20. The capacity of the reservoir for each η is defined as the squared correlation coefficient:

$$C(\eta) = \frac{\mathrm{cov}^2(\vec{y}, \vec{y}_{\mathrm{pred}}(\eta))}{\mathrm{var}(\vec{y})\mathrm{var}(\vec{y}_{\mathrm{pred}}(\eta))}, \tag{3}$$

which takes a value of 1 for perfect prediction and 0 for worst prediction. The overall performance is quantified by the normalised sum of all capacities [5]:

$$C_{\Sigma} = \frac{1}{20}\sum_{\eta=1}^{20} C(\eta). \tag{4}$$

III. Results

A. Characterising chaos in the TFIM

We first characterise the chaotic behaviour of the TFIM by analysing its spectral statistics. For a system with eigenenergies E_n, the distribution of level spacings $s_n = E_{n+1} - E_n$ distinguishes between integrable (Poissonian) and chaotic (Wigner-Dyson) dynamics [13]. This is quantified by the mean level spacing ratio $\langle r\rangle = \langle \min(s_{n+1}, s_n)/\max(s_{n+1}, s_n)\rangle$, which is $2\ln(2) - 1 \approx 0.386$ for Poisson and $4 - 2\sqrt{3} \approx 0.535$ for the Gaussian Orthogonal Ensemble (GOE), a subclass of Wigner-Dyson statistics [13]. We also probe chaos in the time domain using the spectral form factor (SFF):

$$K(t) = \overline{\sum_{n,m} e^{i(E_m - E_n)t}}/\mathcal{N}^2, \tag{5}$$

where $\mathcal{N}$ is the Hilbert space dimension [8, 14]. Chaotic systems exhibit a characteristic "ramp-plateau" profile in the SFF. The Thouless time t_{Th}, marked by the start of this universal ramp, is a timescale for the onset of RMT behaviour.

B. QRC Performance, chaos and observable dynamics

Prior work suggests that QRC performance peaks at the "edge of chaos" [8, 15, 16]. For the TFIM, this would imply optimal performance for evolution times Δt just before t_{Th} and for h preceding the chaotic regime.

Our results confirm this in the absence of quantum back-action ($g = 0$). As shown in Figure 1, the performance, measured by the normalised Sum Capacity of the STM task, peaks for magnetic fields $0.35 \leq h \leq 0.85$, which correspond to $\langle r\rangle \lesssim 0.535$. Furthermore, no variation in performance with changing h is observed for $\Delta t < 1$, as the evolution does not have time to display the system's chaotic behaviour. However, we find a key deviation from the proposed temporal criterion: the optimal Δt is consistently much shorter than t_{Th}, suggesting that for intermediate scramblers like the TFIM, the Thouless time serves as an upper bound rather than a direct predictor for the optimal evolution time.

Beyond the transition controlled by h[13], the dynamical timescale Δt determines whether observables retain useful information. For instance, Figure 2 shows the temporal variance of $\hat{\sigma}^x$ observables for $h = 1.05$, revealing intervals where the variance collapses to near zero. We find that the last Δt before variance collapses in both

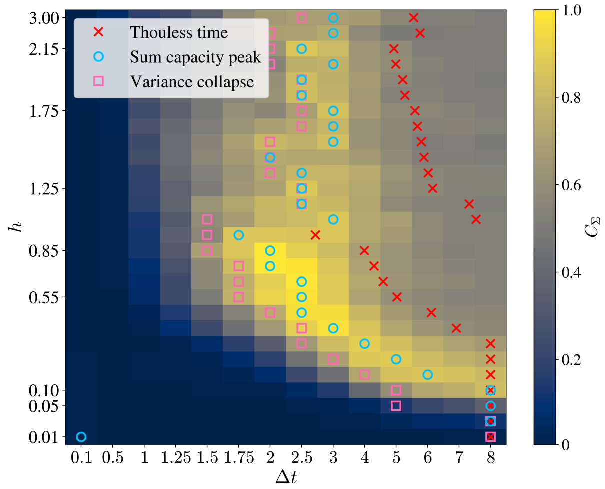

FIG. 1: Heatmap of normalised Sum Capacity for the STM task as a function of evolution time Δt (x-axis) and magnetic field h (y-axis) for the TFIM reservoir under projective measurement ($g = 0$). Colour intensity represents the normalised sum capacity (scale shown), with brighter regions indicating higher memory performance. For each h, blue circles mark the Δt yielding maximum capacity, red crosses indicate the Thouless time t_{Th} (theoretical upper bound), and pink squares denote the variance collapse time (empirical lower bound).

the z basis and at least one orthogonal basis (x or y) serves as an empirical lower bound for optimal performance (Figure 1). Together with the Thouless time as an upper bound, this defines a functional window for Δt where the reservoir is neither frozen nor fully scrambled.

C. Impact of weak measurement back-action

Introducing weak measurements with quantum back-action ($g > 0$) significantly alters the performance landscape. With the optimal back-action strength $g_{\text{opt}} = 0.256$ found in [5], performance improves at shorter evolution times Δt compared to the $g = 0$ case (Figure 3). This trend continues with stronger back-action ($g = 0.5$, Figure 4). The optimal parameters shift further towards shorter Δt and higher magnetic fields ($0.75 \leq h \leq 1.15$), moving the system away from the integrable-chaotic boundary and into the regime of intermediate $\langle r\rangle$ values. This challenges the universality of the "edge of chaos" criterion in the presence of quantum back-action.

D. Fully chaotic limit

To test the limits of chaos, we replaced the TFIM with a Hamiltonian drawn from the Gaussian Unitary Ensemble, resulting in a fully chaotic reservoir with a very short Thouless time $t_{Th} \sim 0.35$ [14]. As shown in Figure 5, the STM performance for this Haar-random system is poor and invariant for $\Delta t > t_{Th}$. This confirms that deep chaotic regimes are detrimental to memory tasks, as rapid information scrambling makes past inputs unrecoverable from local observables. Besides, such dynamics

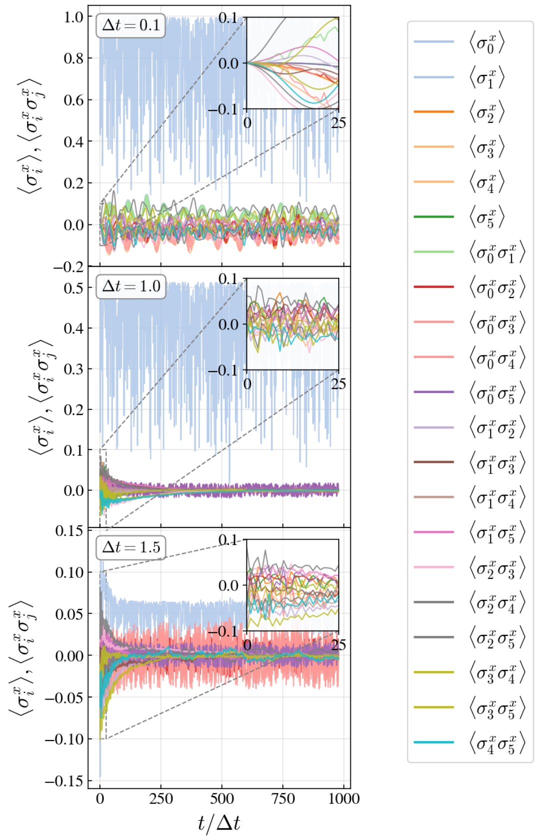

FIG. 2: Evolution of observables measured in the x basis over the full QRC trajectory for $h = 1.05$. Each panel corresponds to a different evolution time: $\Delta t = 0.1$, $\Delta t = 1.0$, $\Delta t = 1.5$. Observables are plotted across all reservoir qubits, with $\langle\hat{\sigma}_0^x\rangle$ consistently showing the largest variance, likely due to its direct coupling to the input signal.

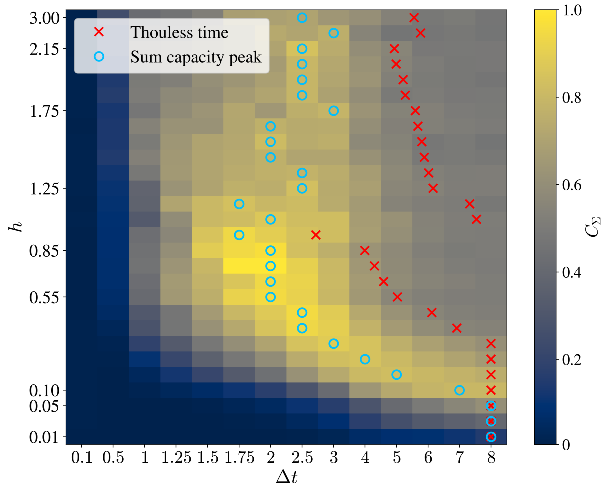

FIG. 3: Normalised Sum Capacity for the STM task as a function of Δt and h under weak measurement with optimal back-action strength $g = 0.256$ [5]. Compared to the projective case ($g = 0$), performance improves at shorter Δt and shifts toward higher magnetic fields (stronger chaos).

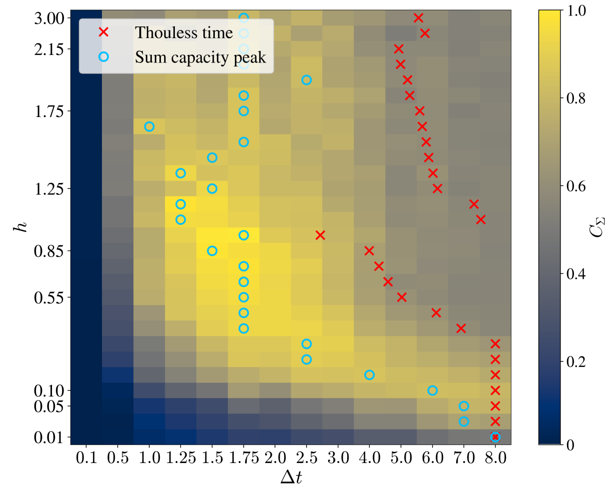

FIG. 4: Normalised Sum Capacity for the STM task with increased back-action strength $g = 0.5$. As back-action strengthens, the optimal performance region continues to shift toward shorter evolution times and higher magnetic fields ($h \gtrsim 0.75$). This trend further challenges a universal "edge of chaos" criterion, underscoring that measurement strength actively redefines the reservoir's effective operational window relative to its underlying chaotic transition.

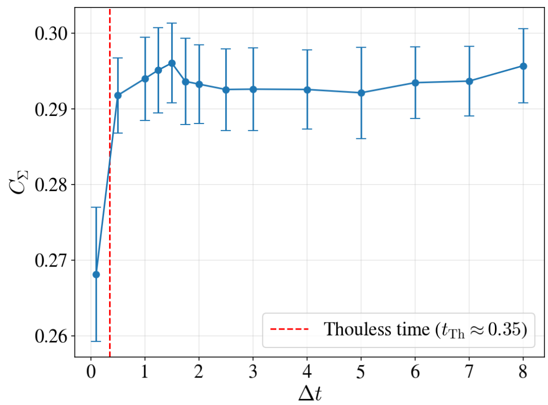

FIG. 5: Normalised Sum Capacity for the STM task using a fully chaotic Haar-random reservoir. The performance is low and nearly constant for $\Delta t > t_{Th} \approx 0.35$ (red dashed line), illustrating that deep chaotic regimes, characterised by rapid scrambling and short Thouless times, are detrimental to memory tasks. Error bars correspond to the standard deviation of the mean over reservoir realisations.

lead to exponential concentration of observables, rendering them unresolvable with finite measurements [12].

IV. Conclusions

This work has systematically investigated the relationship between quantum chaos, information scrambling and computational performance in quantum reservoir computing, studying physical timescales to guide the selection of the key hyperparameter, the evolution time Δt.

Our study of the TFIM reservoir confirms that a non-maximally chaotic regime yields optimal memory performance, with peak normalised Sum Capacity occurring at intermediate magnetic field strengths. Furthermore, we identify two distinct constraints on the evolution time Δt as a performance indicator for such intermediate scrambling systems. First, we demonstrate that the Thouless time is not a reliable indicator of peak performance; instead, it serves as a practical upper bound, beyond which rapid information scrambling degrades memory. Second, at short evolution times, we observe temporal variance collapse, a dynamical freezing of observables that suppresses temporal fluctuations and limits their usefulness for training, thereby defining an empirical lower bound on Δt. Peak performance consistently occurs within this bounded functional window.

Furthermore, we showed that the introduction of weak measurement back-action fundamentally reshapes this relationship. By enabling continuous operation, quantum back-action not only improves performance at shorter evolution times but also shifts the optimal operational regime towards stronger magnetic fields, moving it away from the standard integrable-chaotic boundary. This challenges the universality of a simple "edge of chaos" criterion and underscores the role of measurement as an active component in the reservoir's dynamics.

Finally, our results establish clear limits: deep chaotic regimes, exemplified by Haar-random dynamics, are detrimental to memory capacity. In such systems, rapid information scrambling delocalises input information into complex many-body correlations. Combined with exponential concentration, this renders past inputs irretrievable via the one- and two-body observables used in the readout, leading to poor and static performance.

In conclusion, while physical timescales like the Thouless time guide hyperparameter selection in QRC, achieving optimal performance requires a balanced interplay between the system's native chaos and the specific measurement protocol. The most effective quantum reservoirs are not those that are maximally chaotic, but those whose information scrambling dynamics are carefully tuned to the task and measurement protocol at hand, avoiding both premature observable freezing and excessive information delocalisation.

Acknowledgments

I would like to express my sincerest gratitude to Dr Pere Mujal and Giacomo Franceschetto for their guidance and support throughout this project, as well as Prof. Dr Antonio Acín for welcoming me to the Quantum Information Theory group at the Institute of Photonic Sciences, thanks to the SPIE@ICFO Maria Yzuel Fellowship.

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La finestra de temps operacional per a la computació de reservori quàntic més enllà de la vora del caos

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Resum: La computació de reservori quàntic aprofita la dinàmica quàntica complexa per processar dades temporals; no obstant això, la selecció dels seus hiperparàmetres, com ara el temps d'evolució del sistema, sovint és heurística i manca de fonament físic. Aquest treball investiga el comportament caòtic quàntic com a criteri per escollir aquest temps d'evolució, utilitzant un model d'Ising de camp transversal com a reservori. Tot i que el rendiment assoleix un màxim a l'anomenada vora del caos pel que fa a la intensitat del camp magnètic, el temps d'evolució òptim se situa dins d'una finestra funcional fitada per dues escales de temps diferents: una fita inferior, que introduïm aquí, definida pel col·lapse temporal de les variàncies dels observables, i una fita superior donada pel temps de Thouless. Cal remarcar que el temps òptim és consistentment més curt que el temps de Thouless, que establim com una fita superior i no com un objectiu directe, en contra del que suggerien estudis previs. A més, la introducció de la retroacció de la mesura desplaça aquest règim òptim, posant en qüestió la noció d'una regla universal de la vora del caos. Els nostres resultats demostren que una computació de reservori quàntic efectiva requereix un equilibri matisat entre caos, temps d'evolució i intensitat de mesura, i que els sistemes completament caòtics resulten perjudicials per a tasques de memòria.
Paraules clau: Aprenentatge automàtic quàntic, computació de reservori quàntic, informació quàntica, caos quàntic, barreja d'informació, concentració exponencial.
ODSs: Aquest TFG s'alinea amb l'ODS9 (Indústria, innovació, infraestructures).

Objectius de Desenvolupament Sostenible (ODSs o SDGs)

1. Fi de la es desigualtats		10. Reducció de les desigualtats	
2. Fam zero		11. Ciutats i comunitats sostenibles	
3. Salut i benestar		12. Consum i producció responsables	
4. Educació de qualitat		13. Acció climàtica	
5. Igualtat de gènere		14. Vida submarina	
6. Aigua neta i sanejament		15. Vida terrestre	
7. Energia neta i sostenible		16. Pau, justícia i institucions sòlides	
8. Treball digne i creixement econòmic		17. Aliança pels objectius	
9. Indústria, innovació, infraestructures	X		

Aquest Treball de Fi de Grau s'alinea amb l'ODS9 (Indústria, innovació, infraestructures), ja que explora dinàmiques quàntiques en un algorisme d'aprenentatge automàtic, contribuïnt a l'àrea de la computació i la informació quàntica.