

The Representability Gap: Massive-Graviton Physics Cannot Be Held by Virtual-World Physics Engines but Survives the Low-Precision Number Formats of Artificial Intelligence

Alfredo Merlet

alfredo.merlet@gmail.com

Universidad del Alba <https://orcid.org/0009-0007-8558-164X>

Research Article

Keywords: massive graviton, floating-point arithmetic, physics engines, metaverse, virtual reality, low-precision deep learning, gravitational waves, numerical representability

Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11445510/v1>

License:  This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

The Representability Gap: Massive-Graviton Physics Cannot Be Held by Virtual-World Physics Engines but Survives the Low-Precision Number Formats of Artificial Intelligence

Alfredo Agustín Merlet Echavarría^{1,2,3}

¹ Universidad del Alba, Santiago, Chile (Lecturer). ² Instituto Profesional IACC, Santiago, Chile (Lecturer). ³ Doctoral Programme in Strategic Management and International Business, Universidad de Sevilla, Seville, Spain (PhD candidate).

ORCID: 0009-0007-8558-164X · Correspondence: alfredo.merlet@gmail.com

Abstract

Background. The graviton, the hypothetical quantum of gravity, is often invoked in speculation about future artificial intelligence (AI) and immersive virtual worlds, yet a single graviton is widely regarded as undetectable and its only quantified observable property is an upper bound on its mass. Whether massive-graviton physics could even be represented inside the computational systems that run virtual worlds and AI has not been tested. **Methods.** Two computational experiments with known truth were run. Experiment 1 asks whether the Yukawa correction implied by a graviton at the current 90% credibility bound ($m_g \leq 2.42 \times 10^{-23} \text{ eV}/c^2$) is representable in six floating-point formats, using a 60-digit reference, a naive in-format evaluation, and a velocity-Verlet orbit integrator of the kind used in physics engines. Experiment 2 injects the massive-graviton dispersion phase into noise-free inspiral waveforms and measures, for each format, the ratio between the time-and-phase-aligned dispersion residual and the rounding error, and the test AUC of a neural-network discriminator trained on rounded inputs (90 training runs). **Results.** The correction is unrepresentable at every virtual-world scale: it first becomes storable in float64 at $5.4 \times 10^8 \text{ m}$ and in float32 at $1.25 \times 10^{13} \text{ m}$ (about 84 AU). Naive in-format evaluation manufactures phantom corrections up to 9×10^{16} times the true value, and a float32 orbit at 1 AU deviates by 834 km where the true effect is 8 m. In AI formats the opposite holds: at the bound every format, including 8-bit FP8, preserves the residual (representational SNR 9.7 to 2×10^7), with representational floors 3 to 4,500 times below the bound for formats from FP8 to float32; classifier accuracy did not degrade with precision. **Conclusions.** Precision is the binding constraint for virtual-world engines but not for AI, where noise and learnability bind first. Any claim that a graviton-scale effect appears in a simulated world should be accompanied by an explicit representability check.

Keywords: massive graviton; floating-point arithmetic; physics engines; metaverse; virtual reality; low-precision deep learning; gravitational waves; numerical representability

1. Introduction

The graviton occupies an unusual place in contemporary technology discourse. It is the hypothetical spin-2 quantum of the gravitational field, it has never been observed, and there are strong arguments that a single graviton cannot be detected by any realistic experiment (Dyson 2013; Rothman and Boughn 2006). At the same time, popular and speculative accounts increasingly connect quantum gravity to two technologies that

are themselves fast-moving: artificial intelligence (AI) and immersive virtual environments, from virtual and augmented reality to the so-called metaverse (Dionisio et al. 2013). The question that motivates this article is therefore deliberately sober: *through what measurable channel could graviton physics influence the development of AI and of virtual worlds at all?*

A direct physical channel can be set aside at the outset. The coupling of a single graviton to matter is so weak that no device built for AI or for virtual reality could exchange information through it. What remains is an epistemic channel. If the graviton has a small rest mass m_g , gravity acquires a finite range and gravitational waves become dispersive, and both effects are calculable (Will 1998; de Rham 2014; de Rham et al. 2017). The current strongest bound, obtained by the LIGO, Virgo and KAGRA collaborations from the dispersion of gravitational waves in the GWTC-3 catalogue, is $m_g \leq 2.42 \times 10^{-23} \text{ eV}/c^2$ at 90% credibility in the published version (Abbott et al. 2025); an earlier preprint version reported $1.27 \times 10^{-23} \text{ eV}/c^2$ (Abbott et al. 2021). Virtual worlds simulate gravity with physics engines, and AI systems learn physics from data stored and computed in reduced-precision number formats (Micikevicius et al. 2018, 2022; Kalamkar et al. 2019). Massive-graviton physics can influence these technologies only if it can first be *represented* in their arithmetic.

This article tests that precondition. It introduces the **representability gap**: the distance between the size of a physical effect and the smallest difference a given number format can hold at the relevant scale. The gap is measured in two experiments with known truth. Experiment 1 asks whether the Yukawa correction implied by a graviton at the bound can be stored and computed in the floating-point formats used by physics engines, and what a naive engine produces when it cannot. Experiment 2 asks whether the dispersion signature of a massive graviton survives rounding to the formats used by modern AI hardware (float32, float16, bfloat16 and the two FP8 encodings), and whether a learned discriminator degrades when trained on rounded inputs. The closest prior work, Chand (2026), benchmarked a deep-learning discriminator against matched filtering for single-event graviton-dispersion tests on real LIGO strain and found that detector noise sets the single-event limit. The present study is complementary: it removes noise altogether and isolates the limit imposed by number representation.

The contribution is threefold. First, it quantifies, for each format and both published bounds, the distance at which a massive-graviton correction first becomes storable, and shows that no virtual-world scale reaches it. Second, it documents a failure mode that matters more than invisibility: naive in-format evaluation manufactures phantom corrections many orders of magnitude larger than the true one. Third, it shows that the same physics is comfortably representable in every AI format examined, so that for AI the binding constraints are noise and learnability rather than precision. The link from these technical results to the governance of simulated worlds is stated in Section 5 as a formal analogy, not as a finding about deployed systems.

2. Background and literature verification

2.1 Massive gravitons and their observable signatures

In linearised massive gravity a graviton of mass m_g modifies the static potential of a point mass from the Newtonian form to a Yukawa form with range equal to the graviton Compton wavelength $\lambda_g = h/(m_g c)$ (de

Rham 2014). In fully non-linear theories, the Vainshtein mechanism screens such deviations near massive sources, so the linearised Yukawa form is an upper envelope on how visible a static correction can be (de Rham et al. 2017). For propagating waves, a massive graviton implies a frequency-dependent group velocity, which imprints an additional phase on a compact-binary inspiral proportional to $1/f$ (Will 1998; Mirshekari et al. 2012). This dispersion test underlies the GWTC-3 bound (Abbott et al. 2025). Detecting individual gravitons is a different and, by current arguments, unreachable goal (Dyson 2013; Rothman and Boughn 2006).

2.2 Floating-point precision in virtual worlds and AI

Floating-point arithmetic stores numbers with a fixed number of significant bits, so the smallest representable relative difference near 1 is set by the machine epsilon ϵ (Goldberg 1991; Higham 2002; IEEE 2019). Real-time physics engines favour single precision for speed, which produces positioning errors and collision artefacts in large worlds (Kaufmann et al. 2021); game-engine platforms used for planetary-scale mapping face the same limitation (Lee 2024), and geometric predicates in virtual environments are sensitive to the numerical representation chosen (Garau et al. 2025). In AI, training and inference have moved from float32 towards 16-bit formats (float16 and bfloat16) and 8-bit FP8 encodings E4M3 and E5M2 (Micikevicius et al. 2018, 2022; Kalamkar et al. 2019). Deep learning is now routine in gravitational-wave astronomy (George and Huerta 2018; Gabbard et al. 2018; Cuoco et al. 2021).

2.3 Literature verification

Novelty was verified with four Scopus queries (title, abstract and keywords) run on 20 October 2026. Table 1 summarises the screening. Wildcard queries on *graviton** retrieved homonyms (the AWS Graviton processor family and a garment-warping model named GraVITON), which were read and excluded one by one. No record connects gravitons with virtual reality, augmented reality, the metaverse or physics engines (Q3), and no record treats the precision limits of physics engines as a limit on which physics can be represented (Q4). The single directly relevant record for AI (Chand 2026) is the anchor against which the second experiment is positioned.

Table 1. Scopus screening funnel (20 October 2026).

Query	Scope	Records	Homonyms	Adjacent	Directly relevant
Q1	graviton* × AI/ML/deep learning/neural networks	21	12 (AWS Graviton/Arm)	8	1
Q2	graviton mass/modified dispersion × gravitational waves × deep learning	1	0	0	1
Q3	graviton* × VR/AR/metaverse/physics or game engines	3	1 (GraVITON)	2	0
Q4	physics/game engines, VR, digital twins × floating point/precision	123	—	119	4

Note. Q1: TITLE-ABS-KEY(graviton* AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*")). Q2: ("graviton mass" OR "massive graviton" OR "modified dispersion") AND "gravitational wave*" AND ("deep learning" OR "neural network*" OR "simulation-based inference"). Q3: graviton* AND ("virtual reality" OR "augmented reality" OR metaverse OR "physics engine*" OR "game engine*"). Q4: ("physics engine*" OR "game engine*" OR "virtual reality" OR "digital twin*") AND ("floating-point" OR "floating point" OR "round-off" OR "numerical precision"). Directly relevant records: Q1/Q2, Chand (2026); Q4, Kaufmann et al. (2021), Lee (2024), Garau et al. (2025), and a 2008 hardware paper on floating-point physics-engine processors without abstract.

3. Methods

3.1 Pre-specified hypotheses

Three hypotheses were fixed before the full runs. **H1:** the Yukawa correction implied by a graviton at the bound is not representable in float32 or float64 at any scale used by virtual worlds (up to planetary scale). **H2:** rounding to low-precision AI formats erases the massive-graviton dispersion residual at the bound (representational SNR below 1). **H3:** a neural discriminator trained on inputs rounded to low-precision formats loses accuracy relative to higher-precision inputs at the bound. A pilot computation made before the full design had already shown a spurious non-zero float64 correction at 10 km, so the phantom-correction analysis (Experiment 1b) is reported as anticipated rather than as a blind prediction.

3.2 Experiment 1: the static Yukawa correction

The graviton Compton wavelength and the Yukawa potential of a central mass M are

$$\lambda_g = h c / (m_g c^2), \quad V(r) = -(G M m / r) \cdot \exp(-r/\lambda_g) \quad (1)$$

so that, with $x = r/\lambda_g$, the force relative to Newton and its fractional deficit are

$$F_Y / F_N = e^{-x} (1 + x), \quad \delta(x) = 1 - e^{-x} (1 + x) = x^2/2 - x^3/3 + O(x^4) \quad (2)$$

A correction is *representable* in a format if the correctly rounded value of $F_Y/F_N = 1 - \delta$ differs from 1. Because the spacing of floating-point numbers just below 1 is $\epsilon/2$, this occurs when δ exceeds about $\epsilon/4$, which gives the threshold distance

$$r^* \approx \lambda_g \cdot (\epsilon/2)^{1/2} \quad (3)$$

E1a (representability). For both bounds ($\lambda_g = 5.12 \times 10^{16}$ m and 9.76×10^{16} m) and six formats (float64, float32, float16, bfloat16, FP8 E4M3, FP8 E5M2), the exact δ was computed with mpmath at 60 significant digits on 301 log-spaced distances from 1 m to 10^{15} m, and r^* was located by bisection on the exact storage criterion. **E1b (naive evaluation).** The expression $1 - e^{-x}(1 + x)$ was evaluated as an engine would, rounding after every operation to the format, and compared with the exact value. **E1c (engine integration).** A test body on a circular orbit was integrated for one period (1,000 steps) with the velocity-Verlet scheme used by many physics engines (Hairer et al. 2003), under Newtonian and Yukawa gravity, in float32 and float64, at seven scene scales from a 10 m room to 1,000 AU. Lengths were expressed in units of the initial radius (a floating-origin convention that avoids float32 overflow of GM at astronomical scales; relative precision is unit-invariant). The true Yukawa-induced displacement was obtained by running the same integrator, with the same step, at 50 significant digits, so that every difference between engine and reference is arithmetic.

3.3 Experiment 2: the dispersion signature in AI number formats

Waveforms follow the stationary-phase inspiral approximation (Cutler and Flanagan 1994) with leading-order amplitude $f^{-7/6}$ and post-Newtonian phase to first order, for a GW150914-like detector-frame source (36 and 29 solar masses, luminosity distance 440 Mpc, $z = 0.09$; Abbott et al. 2016), restricted to 20 Hz up to the innermost-stable-orbit frequency (67.6 Hz). With $v = (\pi M f)^{1/3}$ and symmetric mass ratio η , the phase and the massive-graviton term (Will 1998) are

$$\Psi(f) = 2\pi f t_c - \phi_c - \pi/4 + [3/(128 \eta v^5)] \cdot [1 + (3715/756 + 55\eta/9) v^2] \quad (4)$$

$$\Psi_{\text{MG}}(f) = -\pi D c / [\lambda_g^2 (1 + z) f] \quad (5)$$

where the distance measure D is approximated by the luminosity distance at this low redshift. Time series were generated at 2,048 Hz and the final second before coalescence was kept (2,048 samples), normalised to unit peak amplitude as in machine-learning pipelines.

E2a (representational floor). For 31 log-spaced masses between 10^{-25} and 10^{-22} eV/c² plus both bounds, the massive-graviton template was aligned to the general-relativity template by maximising their complex overlap over time and phase (the constant phase and time shift are unobservable), so that the residual r contains only the physically measurable part of the dispersion. Both templates were then rounded to each format, and the representational signal-to-noise ratio and the implied floor were computed as

$$\text{SNR}_q = \|r\| / \sigma_q, \quad m_g^* = m_{\text{bound}} \cdot \text{SNR}_q(m_{\text{bound}})^{-1/s} \quad (6)$$

where σ_q is the root-mean-square rounding error of the general-relativity template in the given format (for float64, the half-unit-in-the-last-place model) and s is the fitted log-log slope of SNR_q against m_g within the verified grid ($s = 1.9999$, as expected since the residual scales with m_g^2). Where the $\text{SNR}_q = 1$ crossing lies inside the grid, direct interpolation and Equation (6) agree to four significant digits; for float32 and float64 the floor lies below the grid and is extrapolated with Equation (6). The underflow of raw, unnormalised strain (peak 10^{-21}) was also recorded.

E2b (learned discriminator). For five masses (10^{-22} , 5×10^{-23} , both bounds, and 6×10^{-24} eV/c²) and three data seeds, 6,000 training and 2,000 test waveforms were generated, half general relativity and half massive graviton, with nuisance coalescence phase drawn from $U(0, 2\pi)$ and coalescence time from $U(-5, 5)$ ms, and no detector noise. The same waveforms were rounded to each of the six formats and a multilayer perceptron (two hidden layers of 256 and 128 units, Adam, early stopping) was trained on each, giving 90 runs (scikit-learn; Pedregosa et al. 2011). The network computes in float32, so the float64 and float32 input conditions coincide by construction and serve as the high-precision reference. A robustness check re-trained float64 and float32 on one data seed with five new network initialisations each.

3.4 Reproducibility

All code, random seeds, per-run results and figures are deposited (see Data and code availability). Experiments 1 and 2a are deterministic; Experiment 2b uses fixed seeds. Computations used NumPy (Harris et al. 2020), mpmath 1.3.0, ml_dtypes 0.5.1 for bfloat16 and FP8, and scikit-learn 1.8.0, on a single CPU core.

4. Results

4.1 Experiment 1: no virtual-world scale can hold the correction

Table 2 reports the representability threshold for each format. At the published bound the correction first becomes storable in float64 at 5.40×10^8 m, about 1.4 times the Earth–Moon distance, and in float32 at 1.25×10^{13} m, about 84 astronomical units. The bisection thresholds agree with the approximation in Equation (3) to within 1% for float64 and float32. The 16-bit and 8-bit formats require distances of 10^{15} to

10^{16} m, a sizeable fraction of λ_g itself. At the scale of a room (10 m) the true deficit is about 2×10^{-32} and at the scale of a city (10 km) about 2×10^{-26} (Figure 1), about fifteen and nine orders of magnitude below the float64 threshold; even at the radius of the Earth it remains four orders of magnitude below it. H1 is supported.

Table 2. Distance at which the Yukawa correction first becomes representable (r^*).

Format	ϵ	r^* (m), bound 2.42×10^{-23} eV	r^* (m), bound 1.27×10^{-23} eV	r^* / λ_g	Reference scale
float64	2.22×10^{-16}	5.40×10^8	1.03×10^9	1.05×10^{-8}	$1.4 \times$ Earth–Moon distance
float32	1.19×10^{-7}	1.25×10^{13}	2.38×10^{13}	2.44×10^{-4}	84 AU
float16	9.77×10^{-4}	1.14×10^{15}	2.17×10^{15}	0.0223	7,624 AU
bfloat16	7.81×10^{-3}	3.27×10^{15}	6.23×10^{15}	0.0638	21,864 AU
FP8 E4M3	0.125	1.40×10^{16}	2.67×10^{16}	0.274	93,693 AU
FP8 E5M2	0.250	2.07×10^{16}	3.94×10^{16}	0.404	138,195 AU

Note. Thresholds located by bisection on the exact storage criterion using a 60-digit reference. $\lambda_g = 5.12 \times 10^{16}$ m (published bound) and 9.76×10^{16} m (preprint bound). AU, astronomical unit (1.496×10^{11} m).

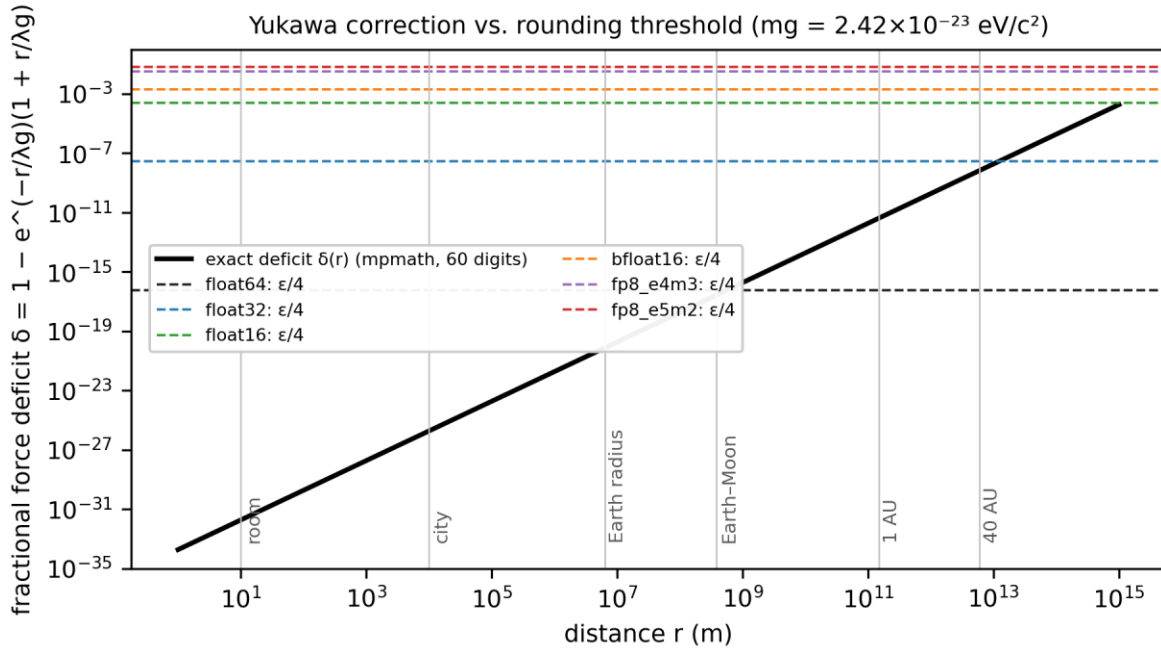


Figure 1. Exact fractional force deficit of the Yukawa (massive-graviton) correction at the published bound, against the rounding threshold $\epsilon/4$ of each format. The correction becomes storable only where the curve crosses a threshold; vertical lines mark reference scene scales.

Invisibility is the benign outcome. Naive in-format evaluation of $1 - e^{-x}(1 + x)$ is dominated by cancellation. In float64 it returns a non-zero correction from 2.5 m onwards in 58 of the 175 grid points at which the true correction is unrepresentable, with a ratio to the true value of up to 9.2×10^{16} ; in float32 the same happens in 22 of 262 such points, from 1.6×10^9 m, with ratios up to 1.3×10^8 (Figure 2). Every phantom value had the sign of a weakened attraction, so it is indistinguishable in sign from the physical effect it imitates.

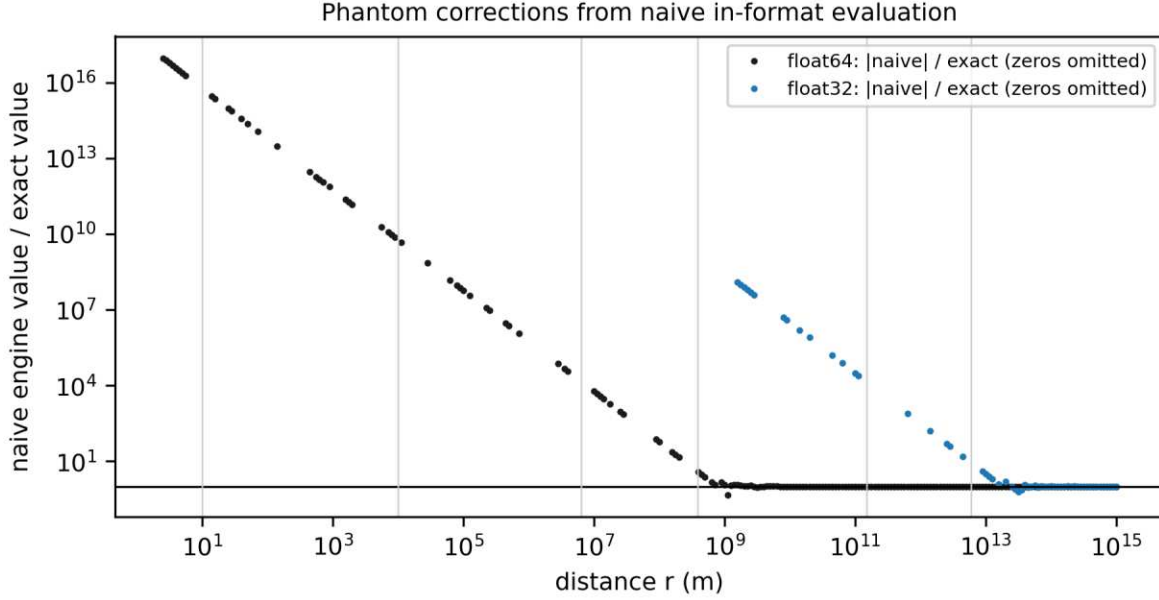


Figure 2. Ratio between the naive in-format value and the exact correction at the published bound (exact zeros omitted). Values far above 1 are phantom corrections produced by cancellation; the ratio converges to 1 only beyond the representability threshold.

The orbit integrations in Table 3 show how the two behaviours reach a physics engine. In float32 the Newtonian and Yukawa runs are bitwise identical at the room, city, planetary and Earth–Moon scales. At 1 AU, however, the float32 engine reports a Yukawa-induced displacement of 834 km after one orbit where the true value is 8.0 m, an amplification of about 10^5 ; at 40 AU it again reports nothing, although the true displacement is 513 km, and only at 1,000 AU does it recover the true value to within 3%. In float64 the engine is exact at and beyond 1 AU but reports phantom displacements 1.4×10^3 and 45 times too large at the planetary and Earth–Moon scales. The response of a single-precision engine to graviton-scale physics is therefore not monotone in scale: it alternates between silence and fabrication before becoming faithful.

Table 3. One-orbit velocity-Verlet integration under Newtonian and Yukawa gravity (published bound).

Scale	Orbit radius (m)	True Yukawa displacement (m)	float64 engine (m)	float64 roundoff drift (m)	float32 engine (m)	float32 roundoff drift (m)
Room	10	2.39×10^{-30}	0	4.91×10^{-13}	0	4.08×10^{-6}
City	1.00×10^4	2.39×10^{-21}	0	4.91×10^{-10}	0	4.08×10^{-3}
Earth radius	6.37×10^6	6.19×10^{-13}	8.73×10^{-10}	3.13×10^{-7}	0	2.6
Earth–Moon	3.84×10^8	1.36×10^{-7}	6.10×10^{-6}	1.89×10^{-5}	0	157
1 AU	1.50×10^{11}	8.01	8.03	7.36×10^{-3}	8.34×10^5	6.11×10^4
40 AU	5.98×10^{12}	5.13×10^5	5.13×10^5	0.294	0	2.44×10^6
1,000 AU	1.50×10^{14}	8.00×10^9	8.00×10^9	7.35	7.82×10^9	6.11×10^7

Note. True displacement from the same integrator and step at 50 significant digits. Engine displacement = distance between the Newtonian and Yukawa runs in the given format; 0 means bitwise-identical trajectories. Roundoff drift = distance between the Newtonian engine run and its 50-digit reference. Results for the preprint bound are in the deposited data.

4.2 Experiment 2: AI formats preserve the dispersion signature

At the published bound the mismatch between general-relativity and massive-graviton templates after optimal alignment is 9.7×10^{-5} , and the aligned residual has a relative norm of 1.2%. Table 4 shows that this residual survives rounding in every format: the representational SNR ranges from 9.7 for FP8 E5M2 to 2.0×10^7 for float32. H2 is therefore not supported. The representational floor, the graviton mass below which a format can no longer hold the residual, lies 3.1 (FP8 E5M2), 4.3 (FP8 E4M3), 17.5 (bfloat16), 49.5 (float16) and about 4,500 (float32) times below the published bound (Figure 3).

Table 4. Representational SNR of the aligned dispersion residual and implied floor on the graviton mass.

Format	ε	SNR _q at published bound	Floor m_g^* (eV/c ²)	Bound / floor	Raw strain (peak 10^{-21}) flushed to zero
float64	2.22×10^{-16}	1.09×10^{16}	2.32×10^{-31} (extrap.)	1.04×10^8	0%
float32	1.19×10^{-7}	2.04×10^7	5.36×10^{-27} (extrap.)	4,516	0%
float16	9.77×10^{-4}	2,451	4.89×10^{-25}	49.5	100%
bfloat16	7.81×10^{-3}	308	1.38×10^{-24}	17.5	0%
FP8 E4M3	0.125	18.7	5.60×10^{-24}	4.3	100%
FP8 E5M2	0.250	9.7	7.77×10^{-24}	3.1	100%

Note. Floors for float16 and lower formats are interpolated inside the verified grid (10^{-25} to 10^{-22} eV/c²) and agree with Equation (6) to four digits; float32 and float64 floors are extrapolated with Equation (6) (slope 1.9999), and the float64 value uses the half-up rounding model because the reference is itself float64.

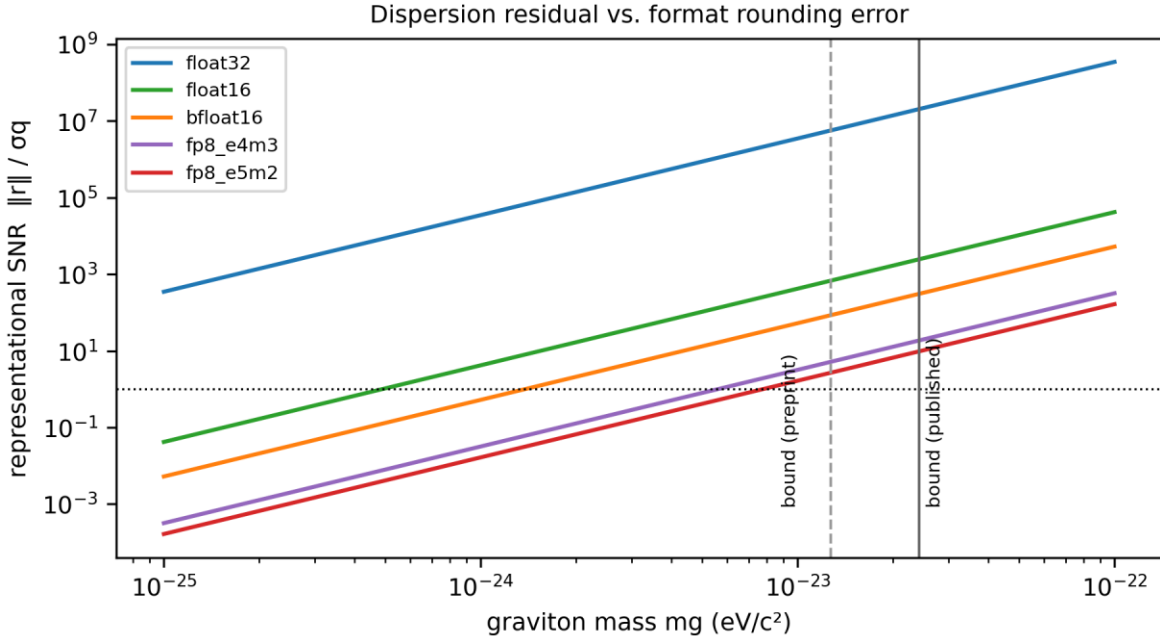


Figure 3. Representational SNR of the time-and-phase-aligned massive-graviton residual for each format. The dotted line marks SNR = 1; solid and dashed vertical lines mark the published and preprint bounds. float64 is off scale (SNR_q $\approx 10^{16}$ at the bound).

There is one caveat on representability that does matter in practice. Raw strain at its astrophysical amplitude (peak 10^{-21}) is flushed entirely to zero in float16 and in both FP8 encodings, because it lies below their smallest subnormal number, whereas bfloat16, which keeps the float32 exponent range, stores it with 0.16%

relative error. The favourable result above holds only after the normalisation that machine-learning pipelines apply routinely.

Table 5 and Figure 4 report the learned discriminator. Above the bound (10^{-22} and $5 \times 10^{-23} \text{ eV}/c^2$) every format reaches an AUC of 1.000 in all seeds. At both the preprint bound and $6 \times 10^{-24} \text{ eV}/c^2$ every format, including the float32 reference, is at chance (AUC 0.49 to 0.51), although Experiment 2a shows that the residual is representable there in all formats. The limit is therefore learnability under nuisance phase and time, not precision. At the published bound one data seed failed in the float32 reference and in FP8 E5M2 (AUC 0.55) while succeeding in the other formats; the robustness check re-trained the reference on that seed with five new initialisations in each input condition, and all ten reached $\text{AUC} \geq 0.99997$, which identifies an optimisation failure rather than a representation effect. H3 is not supported: no systematic loss of accuracy with lower precision was observed.

Table 5. Test AUC of the learned discriminator by graviton mass and input format (mean, min–max over three data seeds; two decimals).

$m_g \text{ (eV}/c^2\text{)}$	float64	float32	float16	bfloat16	FP8 E4M3	FP8 E5M2
1.00×10^{-22}	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)
5.00×10^{-23}	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)
2.42×10^{-23}	0.85 (0.55–1.00)	0.85 (0.55–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	1.00 (1.00–1.00)	0.85 (0.55–1.00)
1.27×10^{-23}	0.50 (0.48–0.51)	0.50 (0.48–0.51)	0.51 (0.50–0.53)	0.50 (0.49–0.51)	0.51 (0.50–0.51)	0.50 (0.48–0.50)
6.00×10^{-24}	0.50 (0.49–0.50)	0.50 (0.49–0.50)	0.51 (0.50–0.52)	0.50 (0.49–0.51)	0.49 (0.48–0.51)	0.50 (0.49–0.50)

Note. Noise-free inspirals with nuisance phase $U(0, 2\pi)$ and time $U(-5, 5)$ ms; 6,000 training and 2,000 test waveforms per run. The network computes in float32, so the float64 and float32 input conditions are identical by construction.

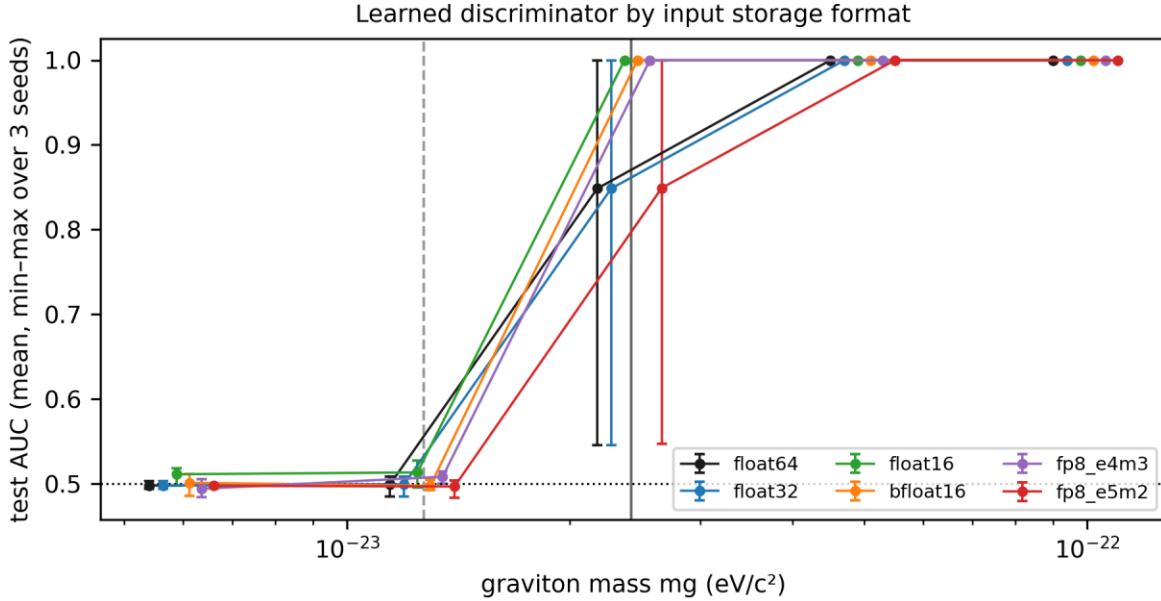


Figure 4. Test AUC of the discriminator by input format (markers offset horizontally for legibility; bars show the range over three seeds). The dotted line marks chance; vertical lines mark the published and preprint bounds.

5. Discussion

The two experiments produce an asymmetry. For the physics engines that run virtual worlds, number representation is the binding constraint: the static signature of a graviton at the bound lies four to fifteen orders of magnitude below what even float64 can hold between the scale of a room and that of a planet, and becomes storable only beyond the orbit of the Moon in float64 and beyond the orbit of Neptune in float32. For AI, number representation is not binding: even 8-bit formats hold the dispersion signature at the bound, so what stands between a learning system and graviton physics is detector noise, as Chand (2026) found on real LIGO strain, and the learnability of the signal under nuisance parameters, as the discriminator results here show. The representability gap is therefore domain-specific, and the answer to the motivating question is correspondingly specific: graviton physics will not reach virtual worlds through their physics engines, while for AI the precision of the hardware is not the obstacle.

The more consequential result is the phantom correction. An engine that evaluates the Yukawa expression naively does not merely fail to show graviton physics; it shows effects that are up to sixteen orders of magnitude too large, with the sign of the real effect, at scales where the real effect cannot exist in the arithmetic at all. A single-precision engine alternates between silence and fabrication as scale grows. By formal analogy, and as a hypothesis for future work rather than a finding about deployed systems, this suggests a requirement for digital twins and for virtual worlds that are marketed as physically faithful, and for AI systems trained on simulator output: claims that a simulated environment exhibits a sub-precision physical effect should carry an explicit representability check, analogous to a units check, before the effect is reported or learned from. The checks used here are cheap: compare the effect with $\varepsilon/4$ at the relevant scale (Equation 3), evaluate small corrections by their series rather than by subtraction, and use a floating origin or double precision where large scales are unavoidable (Kaufmann et al. 2021; Lee 2024).

The study has limitations. The static analysis uses the linearised Yukawa form; Vainshtein screening in non-linear massive gravity would make the correction smaller still, so the thresholds are conservative in the direction of visibility (de Rham 2014). The waveform model is a leading-order inspiral for a single GW150914-like source, without merger, ringdown, spins or detector noise; the dispersion term is partly degenerate with the first post-Newtonian term when masses are free, which is why intrinsic parameters were held fixed. The discriminator is a multilayer perceptron computing in float32, so the experiment tests storage precision of inputs rather than low-precision arithmetic inside the network, and the float64 and float32 conditions coincide. Finally, the bound itself differs between the preprint and published versions of the same analysis; both were carried through, and none of the conclusions depends on the choice.

6. Conclusions

A graviton at the current mass bound cannot be represented by the physics engines of virtual worlds at any scale those worlds use, and naive engines manufacture phantom versions of it many orders of magnitude too large. The same physics is representable in every number format used by modern AI hardware, including FP8, so that for AI the binding limits are noise and learnability. The representability gap offers a simple, quantitative test that any claim about graviton-scale (or other sub-precision) physics in simulated worlds or AI pipelines should pass before it is made.

Declarations

Data and code availability. All code, seeds, per-run results, tables and figures are openly available in Zenodo at <https://doi.org/10.5281/zenodo.23501071> under a CC BY 4.0 licence.

Competing interests. The author declares no competing interests.

Funding. This research received no external funding.

Ethics. Not applicable; the study uses only synthetic data generated by code.

Use of generative AI. Claude (Anthropic) was used to assist with code development, numerical checks, figure preparation and English-language editing. The author designed the study, checked every result against the deposited code and data, verified all references, and takes full responsibility for the content.

References

- Abbott, B. P., et al. (LIGO Scientific Collaboration and Virgo Collaboration) (2016). Observation of gravitational waves from a binary black hole merger. *Physical Review Letters*, 116, 061102. <https://doi.org/10.1103/PhysRevLett.116.061102>
- Abbott, R., et al. (LIGO Scientific Collaboration, Virgo Collaboration and KAGRA Collaboration) (2021). Tests of general relativity with GWTC-3. arXiv preprint arXiv:2112.06861 (version 1). <https://doi.org/10.48550/arXiv.2112.06861>
- Abbott, R., et al. (LIGO Scientific Collaboration, Virgo Collaboration and KAGRA Collaboration) (2025). Tests of general relativity with GWTC-3. *Physical Review D*, 112(8), 084080. <https://doi.org/10.1103/PhysRevD.112.084080>
- Chand, R. (2026). Benchmarking deep learning against matched filtering for single-event graviton-dispersion tests on LIGO data. *Physica Scripta*, 101(41), 416001. <https://doi.org/10.1088/1402-4896/aeb054>
- Cuoco, E., et al. (2021). Enhancing gravitational-wave science with machine learning. *Machine Learning: Science and Technology*, 2(1), 011002. <https://doi.org/10.1088/2632-2153/abb93a>
- Cutler, C., & Flanagan, É. E. (1994). Gravitational waves from merging compact binaries: How accurately can one extract the binary's parameters from the inspiral waveform? *Physical Review D*, 49, 2658–2697. <https://doi.org/10.1103/PhysRevD.49.2658>
- de Rham, C. (2014). Massive gravity. *Living Reviews in Relativity*, 17, 7. <https://doi.org/10.12942/lrr-2014-7>
- de Rham, C., Deskins, J. T., Tolley, A. J., & Zhou, S.-Y. (2017). Graviton mass bounds. *Reviews of Modern Physics*, 89, 025004. <https://doi.org/10.1103/RevModPhys.89.025004>
- Dionisio, J. D. N., Burns, W. G., & Gilbert, R. (2013). 3D virtual worlds and the metaverse: Current status and future possibilities. *ACM Computing Surveys*, 45(3), 34. <https://doi.org/10.1145/2480741.2480751>
- Dyson, F. (2013). Is a graviton detectable? *International Journal of Modern Physics A*, 28(25), 1330041. <https://doi.org/10.1142/S0217751X1330041X>
- Gabbard, H., Williams, M., Hayes, F., & Messenger, C. (2018). Matching matched filtering with deep networks for gravitational-wave astronomy. *Physical Review Letters*, 120, 141103. <https://doi.org/10.1103/PhysRevLett.120.141103>
- Garau, L., Scateni, R., & Cherchi, G. (2025). Triangle-triangle intersections with different numerical representations. In *Proceedings of the 2025 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)* (pp. 401–404). IEEE. <https://doi.org/10.1109/VRW66409.2025.00092>
- George, D., & Huerta, E. A. (2018). Deep neural networks to enable real-time multimessenger astrophysics. *Physical Review D*, 97, 044039. <https://doi.org/10.1103/PhysRevD.97.044039>
- Goldberg, D. (1991). What every computer scientist should know about floating-point arithmetic. *ACM Computing Surveys*, 23(1), 5–48. <https://doi.org/10.1145/103162.103163>

- Hairer, E., Lubich, C., & Wanner, G. (2003). Geometric numerical integration illustrated by the Störmer–Verlet method. *Acta Numerica*, 12, 399–450. <https://doi.org/10.1017/S0962492902000144>
- Harris, C. R., et al. (2020). Array programming with NumPy. *Nature*, 585, 357–362. <https://doi.org/10.1038/s41586-020-2649-2>
- Higham, N. J. (2002). *Accuracy and stability of numerical algorithms* (2nd ed.). SIAM. <https://doi.org/10.1137/1.9780898718027>
- IEEE (2019). *IEEE Standard for Floating-Point Arithmetic* (IEEE Std 754-2019). <https://doi.org/10.1109/IEEESTD.2019.8766229>
- Kalamkar, D., et al. (2019). A study of BFLOAT16 for deep learning training. arXiv preprint arXiv:1905.12322. <https://doi.org/10.48550/arXiv.1905.12322>
- Kaufmann, L. S., Franzin, F. P., Menegais, R., & Pozzer, C. T. (2021). Accurate real-time physics simulation for large worlds. In *Proceedings of the 16th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2021)*, Vol. 1 (pp. 135–142). SciTePress.
- Lee, A. (2024). A novel camera control approach for planetary-scale mapping utilizing game engine technology. *IEEE Access*, 12, 100240–100250. <https://doi.org/10.1109/ACCESS.2024.3409718>
- Micikevicius, P., et al. (2018). Mixed precision training. In *International Conference on Learning Representations (ICLR 2018)*. arXiv:1710.03740. <https://doi.org/10.48550/arXiv.1710.03740>
- Micikevicius, P., et al. (2022). FP8 formats for deep learning. arXiv preprint arXiv:2209.05433. <https://doi.org/10.48550/arXiv.2209.05433>
- Mirshekari, S., Yunes, N., & Will, C. M. (2012). Constraining Lorentz-violating, modified dispersion relations with gravitational waves. *Physical Review D*, 85, 024041. <https://doi.org/10.1103/PhysRevD.85.024041>
- Pedregosa, F., et al. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.
- Rothman, T., & Boughn, S. (2006). Can gravitons be detected? *Foundations of Physics*, 36(12), 1801–1825. <https://doi.org/10.1007/s10701-006-9081-9>
- Will, C. M. (1998). Bounding the mass of the graviton using gravitational-wave observations of inspiralling compact binaries. *Physical Review D*, 57, 2061–2068. <https://doi.org/10.1103/PhysRevD.57.2061>