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Does Human Effort Have Value of its own When AI Can Produce Comparable Creative Work

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ABSTRACT

If artificial intelligence can imitate human creative work, what remains of the value of human effort? This review separates three answers. Effort may signal quality (epistemic value), give the worker a claim to payment (normative value), or give the worker meaning and motivation (experiential value). Eight studies that compare human-made and AI-made work show that telling people a work is AI-made often lowers their ratings and their belief that effort went into it. They do not show that those beliefs cause lower payment, and a human label rarely raises value above a neutral baseline. The evidence for deservingness is thin, the evidence for meaning rests on one experiment, and studies in which people risk real money disagree. The review therefore concludes that the evidence does not establish an independent money value of human effort, and it proposes experiments that could separate the three channels.

Keywords: *Creative Work, Effort Heuristic, Generative Artificial Intelligence, Perceived Effort, Willingness*

1. INTRODUCTION

Suppose an AI system can write a short story, paint a picture or design a small game that most people cannot tell from a person's work. The weeks of effort behind the human version no longer show in the result, and a question that economists have seldom needed to ask becomes difficult to avoid: if effort can no longer be observed in the product, on what basis does it retain value?

There are three possible answers, and they predict different things. The first is that effort is a signal of quality. Work that took time and skill is usually good, so knowledge of the effort tells a buyer what to expect. The second is that effort gives the worker a claim. Many people consider that someone who worked hard deserves a reward, even when a machine's result is no worse. The third is that effort matters to the worker. Making something can bring pride and meaning whether or not buyers pay more for it. This paper calls these epistemic, normative and experiential values.

This distinction matters because most studies do not draw it. They inform participants that a work was made by a human or by AI and record the reaction, but a single label can change beliefs about quality, fairness and authenticity at once. A gap between labels therefore cannot show which belief produced it. Three further distinctions are needed to interpret the evidence. What people believe about effort differs from the effort actually spent, because a label can change the first without the second. A gap between a human label and an AI label cannot show whether human authorship raised value or AI authorship lowered it, unless the study includes a neutral comparison. And what people say differs from what they pay, which in turn differs from what happens in real markets.

This review asks whether existing evidence can separate the three answers. It adds no new data. It examines what each study can and cannot establish, and it concludes with experiments that could distinguish between the answers. It does not assume that human effort commands a premium, and it treats evidence against a premium as seriously as evidence for one.

2. REVIEW METHODOLOGY

This paper uses a selective narrative review of research on how people perceive and value human-created and AI-generated work. Sources were identified through online searches and reference lists of relevant studies. Eight core studies were selected based on their relevance to authorship, perceived effort, valuation and willingness to pay (Abel & Johnson, 2025; Bellaiche et al., 2023; Conlon & Schwardmann, 2026; Horton et al., 2023; Jacobs et al., 2026; Lim et al., 2026; Mandel & Imas, 2026; Neef et al., 2025).

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Each study was examined in terms of what it compared, whether it included a neutral baseline, how effort was measured and whether its outcomes involved opinions or actual payments. The findings were then compared across the three types of value discussed in this paper. Results were not combined statistically because the studies used different methods, creative works and measures.

The review is selective rather than systematic, so it may not include all relevant research.

3. THEORETICAL FRAMEWORK

Epistemic value treats effort as information. If effort usually produces better work, then knowing that someone spent it helps a buyer who cannot judge quality directly. This is the logic of the effort heuristic, the tendency to judge work as better when it is believed to have taken more effort (Kruger et al., 2004), and it implies that effort should matter most where quality is hard to observe. Normative value treats effort as a reason for reward. It implies that effort should matter even when the work is known to be no better, and that it should depend on who receives the money. Experiential value belongs to the worker. Effort can bring pride, meaning and motivation, so this channel predicts effects on producers that do not depend on what buyers pay.

In practice, a single label can affect all three channels at once. Calling a painting AI-made may lower beliefs about effort, make payment seem less fair and make the work appear less authentic, so a lower price cannot reveal which of these is responsible. Two rival explanations complicate matters further. Authenticity, the sense that work comes from a person's own expression, and scarcity, the value of a one-of-a-kind object, can each produce a premium for human work without effort playing any role.

Three earlier literatures clarify these channels. They were developed mostly with humanmade goods, so what follows are hypotheses about AI and not findings. The first is the labor illusion. Buell and Norton (2011) found that people valued an online service more when it displayed the work it was doing. Authorship labels inform people about effort but do not allow them to observe it, so a test in which buyers watch the making would show whether visible effort raises payment more than asserted effort. The second is authenticity. Newman and Bloom (2012) found that people value originals above identical copies because of the object's link to its maker, which suggests that an AI label might lower value by severing that link and not by implying less work. Fuchs et al. (2015) add perceived love as a third candidate, and found that it produced a premium for handmade goods even after they controlled for effort and quality. The authenticity explanation should therefore be divided into essence, love and scarcity. The third literature concerns meaning in work. Ariely et al. (2008) found that people asked for higher pay to keep working when their work was ignored than when it was acknowledged, and Norton et al. (2012) found that people value what they build themselves more, but only when they complete the task. Both suggest that a worker's pride depends on doing the work and on having it acknowledged.

4. EMPIRICAL EVIDENCE

4.1 Labels: a penalty, a premium or neither

Telling people that work is AI-made often lowers their ratings, particularly of skill and value, but the size of the effect depends on what it is compared with. Horton et al. (2023) ran six experiments with 2,965 people and found that paintings labelled AI-made were rated less skilful and less valuable, even though labels were assigned at random. Bellaiche et al. (2023) found the same in two studies (N = 149 and 148) in which all 30 paintings were AI-made and each person saw about half labelled human and half labelled AI. The human label received higher ratings for liking, beauty, profundity and worth, with small differences for liking and beauty ($d = 0.17$ and 0.22) and a moderate one for worth ($d = 0.61$). These were hypothetical ratings, and they show a difference between labels without revealing its source.

The setting matters considerably. Neef et al. (2025) tested 952 people in a representative German sample. Those who saw only one label gave similar ratings whichever it was, while those who saw both rated the human-labelled images about a fifth to a quarter of a standard deviation higher. Jacobs et al. (2026) found the same split: with one label at a time, including no label, there was no reliable effect, but when people chose between two works they preferred the human-labelled one. The design of Bellaiche et al. (2023) showed both labels to everyone, which fits this pattern. The penalty may therefore be partly produced by the act of comparison.

A neutral baseline clarifies the picture. Lim et al. (2026) showed 618 South Korean viewers one of two short human-made clips under an AI label, a human label or no label. Perceived effort averaged 3.48 with the AI label, 4.19 with no label and 4.40 with the human label, and only the AI label differed from the unlabelled clip. This is consistent with people assuming human authorship unless told otherwise, so that a human label adds little while an AI label takes something away. This is only one interpretation, since an unlabelled condition is never fully neutral and two clips from one country cannot establish that the result generalises.

The clearest pattern, then, is an AI-label penalty when human and AI work are compared, while a human-label premium over a neutral baseline is rarely found. None of these designs shows which kind of value produced the gap.

4.2 Effort as a signal of quality

Labels clearly change beliefs about effort. In the fourth experiment of Horton et al. (2023) the same painting was estimated to have taken 18 hours when labelled AI-made and 36 hours when labelled human-made, alongside a lower estimated price ($112 against $148), and Lim et al. (2026) found a similar fall in perceived effort. These results show that the label changed the belief and not the effort itself, but they do not show that the belief caused the lower value. Horton et al. report both numbers without testing a link between them, Lim et al. measured no valuation, and a label also changes beliefs about skill and authenticity.

The second study of Bellaiche et al. (2023) comes closest to testing the link, and it does not support a simple effort premium. Human-labelled works were seen as taking more effort and time. However, according to the authors' plots, the human advantage in liking and beauty appeared only at the top effort rating, while at low and moderate ratings the AI-labelled paintings were liked more. Perceived effort also predicted worth strongly under either label. Because these are hypothetical ratings and the final model was not in the preregistration, they show that effort beliefs accompany value but not that they cause it.

The two studies that measured payment point towards quality and not authorship. In Abel and Johnson (2025), a one standard deviation higher quality score was associated with about 4.8 cents, or 27%, more willingness to pay. In Conlon and Schwardmann (2026), ratings of how fun, creative and polished a game was predicted bids closely, and the AIdesigned games were rated higher and drew higher bids, while disclosing the source to bidders changed nothing. When people can play a game and judge it directly, an effort signal has little left to add. This fits the quality-signal logic, but it is not a real test of it, because no study varied how easy quality was to judge.

4.3 Effort as a reason for reward

Direct evidence that people pay more because effort deserves reward is thin. The cleanest test is in the third study of Conlon and Schwardmann (2026), where people told that a game was human-designed were either told that their payment would go to the designer or that it would not. Bids did not differ between these groups, or from a group told only the source ($p = .87$), and AI games earned at least as much in every group. Two limits apply: the human designers had also used AI, and the AI games were better. The test also concerns payment to one stranger in a small market and not fairness in general.

The remaining evidence is indirect. In Abel and Johnson (2025), 63.9% of those who said they would pay more for a human story gave writers' livelihoods as a reason, yet their actual bids did not differ by label. Lim et al. (2026) interpret one path from perceived effort to intentions to like, save or follow content as reciprocity, and find that the AI label weakened it. But reciprocity was inferred and not measured, and the outcome was an intention to engage and not a payment.

4.4 Effort as meaning for the worker

Only one study examines the worker. Conlon and Schwardmann (2026) had 476 people design games with an AI assistant, and most valued the experience: 80.7% of amateurs were at least moderately proud of their game and 87.5% at least moderately enjoyed designing it. Workers who had watched the AI design a game on its own then showed slightly lower pride (0.14 standard deviations, $p = .05$) and were slightly less willing to pay to post their game publicly (0.13, $p = .05$), while enjoyment and the value placed on the job did not change. The authors describe this as suggestive, and the caution is warranted: the effects sit at the edge of significance, come from a secondary analysis of a short online task, and were not designed to test meaning. Still, the channel matters because it does not depend on what buyers pay. If it is real, buyers could show no premium while workers lose something that prices never record.

4.5 From stated value to real payment

Stated values often show a penalty for AI-labelled work, but stating a value costs nothing. In Horton et al. (2023), people estimated lower gallery prices for AI-labelled paintings, although a human-labelled painting seen after an AI-labelled one was not reliably priced higher ($153 against $148). In the German and later studies above, the penalty appeared only when both labels were seen. When real money is at stake, three studies reach different conclusions.

Abel and Johnson (2025) asked 654 people to read half of a GPT-4 story, credited either to a named, acclaimed author or to ChatGPT. The AI label lowered quality ratings by about 0.28 standard deviations, yet the amount people would forgo in cash or unpaid work to read the ending differed by less than 0.05, and effects larger than about 0.18 were ruled out. The stakes were a few cents, choices were private and only one text was used. A rough calculation from the paper's own figures suggests that the quality drop alone would cut payment by only about 1.3 cents, roughly one standard error, so the null result cannot rule out a small effect that works through quality. This is an illustration and not a finding.

Conlon and Schwardmann (2026) built a small market in which people designed games with an AI assistant and others bid up to $1 of their own money for them. Games made by the AI alone drew higher bids than games by amateurs (47 against 37 cents, 0.31 standard deviations) and by professionals (0.16). Naming the source made no difference: the AI advantage was 6.8 cents with the source hidden and 6.0 with it shown ($p = .79$). Two features limit what this shows. The "human" games were made by people who used AI, so the study tests human involvement alongside AI and not purely human work, and the AI games were better. Even so, this market shows no evidence of a human premium.

Mandel and Imas (2026) ran four preregistered auctions (666 people) for prints of artworks and poems, with a one-in-ten chance that bids were paid for real. The works were identical and differed only in the AI involvement described, and even a small amount of AI lowered bids: a work in which AI filled in a tiny part was valued 21.3% below the fully human version, and fully AI work lost 21.9% in another experiment. Two appendix results soften this. For mass-produced works the human–AI difference was not significant after correction, and adding a small AI part lowered single-copy bids only marginally. The authors interpret the pattern as a special premium for purely human work. But participants saw the whole range of descriptions, the artist and AI tool were fictional, and no work lacked authorship information, so a premium for human work cannot be separated from a penalty for any AI use.

5. DISCUSSION

Three conclusions are reasonably well supported. People often rate AI-labelled work lower and believe it took less effort, especially when they compare it with human work. A human label seldom lifts value above a neutral baseline. And expressing a value for human work is not the same as paying for it, as Abel and Johnson (2025) show: one label lowered ratings while leaving real payment almost unchanged. What the evidence does not show is that effort causes any of this, or that effort creates a price premium of its own.

The explanation lies largely in research design. Most studies change a label, and a label moves beliefs about quality, effort, fairness and authenticity together. Even the best designs isolate only one component. Horton et al. (2023) hold the work constant but do not test effort beliefs. Conlon and Schwardmann (2026) vary who is paid, which isolates deservingness, but their human designers used AI. Mandel and Imas (2026) vary exclusivity, which points to scarcity, but cannot separate a human premium from an AI penalty. No study varies effort, the visibility of quality, the payee and exclusivity together.

This also helps to explain why appreciation and payment diverge. Rating costs nothing, whereas paying does. Payment may follow perceived quality, which may not fall much when the work is good even if people believe less effort went into it. Private choices may be worth less than public ones, and a single small purchase may involve too little at stake for an abstract concern about effort to matter. The incentivised studies also differ in what "human" means, in the goods, in quality and in stakes. If any AI use removes the premium, a market in which every human designer used AI would show none, and if scarcity drives the premium, goods that can be copied for free would show less of it. These are hypotheses, since no study varies them together.

Three implications follow. "The value of human effort" is not a single quantity: it has a buyer side and a worker side, and AI may affect them differently. It can weaken effort as a signal of quality by producing polish without effort, leave deservingness untouched, and still lower a worker's pride. A missing price premium would not show that effort has no value either, because a worker's experience never appears in prices. Finally, future studies should state which kind of value they are testing, since each makes a different prediction.

6. PROPOSITIONS AND FUTURE RESEARCH

The framework yields three propositions, which are hypotheses and not findings. The first is epistemic: the premium for human work should shrink or vanish when buyers can judge quality directly, and effort information should raise payment only as far as it changes beliefs about quality. The second is normative: the premium should persist when buyers are told that the work is no better, and grow when payment goes to the maker or is voluntary. The third is experiential: workers whose work is mostly done by AI should show less pride, motivation and willingness to continue, even with the same pay, whatever buyers pay. A rival proposition holds that if the premium reflects scarcity, authenticity or perceived love and not effort, it should shrink for mass-produced work and persist when effort information is hidden.

One buyer experiment could test all four. Participants would bid real money, at meaningful stakes, for works of matched quality that viewers cannot tell apart, made by a person alone, a person with AI or AI alone. Each work would appear with no label, an accurate label, or an accurate label plus a description of the effort, and some would come with a time-lapse of the making so that effort is observed and not only asserted. Some buyers would be told that the work is no better, or that payment goes to the maker, and works would be offered as one copy or one of many. Afterwards, buyers would rate effort, quality, authenticity and love. The pattern of bids would then point to a channel. A gap that vanishes once quality ratings are held fixed points to quality. A gap that survives the "no better" message points to reward. A gap that shrinks when works are one of many points to scarcity. Finally, the absence of any gap would point to value that only workers experience. Ratings made after bidding are associations, so any claim about mediation remains correlational.

A worker experiment would give people random amounts of AI help on a creative task for a fixed fee, and either credit their output publicly or not. It would measure effort, pride, enjoyment, how much workers value their own output, and willingness to repeat the task, ideally across several sessions. Neither study would resolve every question. Real effort is hard to vary apart from authorship, and laboratory auctions cannot show how markets behave over time, which would need a later field comparison.

7. LIMITATIONS

This review is limited by its selective literature search, which may have excluded relevant studies. Most available research relies on online participants, digital creative work and small-scale experiments, limiting how far the findings can be applied to real-world markets.

Differences in research methods and measures also make direct comparisons difficult. Some key studies are working papers that have not been peer-reviewed. Furthermore, evidence on the deservingness and personal meaning of human effort remains limited, making firm conclusions difficult.

8. CONCLUSION

If AI can imitate human work, what makes human effort valuable? The evidence supports a cautious, layered answer. People do recognise human effort: AI labels lower beliefs about how much effort went into a work, and those beliefs accompany lower ratings and stated prices, especially when human and AI work are compared. But a human label seldom lifts value above a neutral baseline, and the studies cannot show which kind of value is at work. Effort as a signal of quality is plausible but untested as a cause, and where payment was measured it followed perceived quality. Effort as a reason for reward has little direct support. Effort as meaning for the worker has small, suggestive support from one experiment. When people risk real money the results split. A short story and a games market, in which the human designers also used AI, show no payment gap, while auctions of exclusive art and poetry show lower bids for even slight AI involvement.

The strongest conclusion the evidence allows is that it does not establish an independent money value of human effort, and that appreciating effort is not the same as paying for it. That should not be mistaken for a finding that effort is worthless. The one study of workers suggests that what AI changes first may be what prices record least: the pride and meaning of making something. Until the experiments proposed here are run, the value of human effort is best treated as three questions, about quality, about fairness and about the worker, and not as a single price premium.

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