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It is hoped that via this *Showcase* the scholarship on display will reach a wider specialist and non-specialist audience and generate feedback and a scholarly profile for the authors. Every paper in this collection has gone through a rigorous internal review process.

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Ornithological Identification from Images Using Convolutional Neural Networks

By Jialin Wang

AUTHOR BIO

Jialin Wang is a current high school senior attending University High School in California. He started programming at the age of nine and has experience in many programming languages, including Python, Java, and C++. Jialin has excelled in many academic fields at school, especially STEM fields such as computer science, math, and physics. Outside of the classroom, Jialin is a member of University High School's Birding Club where he grew an ardent passion about birding and the environment. In the future, Jialin plans on majoring in computer science and using his skills in programming to address environmental problems and achieve sustainability.

ABSTRACT

As society works towards solutions to address environmental concerns, a crucial task emerges: the conservation of species, including avian species, through precise identification and monitoring. This paper shows that it is necessary to develop a quick and efficient way to identify birds in pictures. This project aims to improve the efficiency of bird identification by using a convolutional network to identify 10 distinct species of birds based on their visual representations. The results of the model are good: eventually, the model achieved decent performance indicators, including an accuracy of 0.75, macro average precision of 0.76, and macro average recall of 0.75. These metrics reflect the model's ability to not only correctly identify birds but also minimize false identifications. Notably, this model demonstrates remarkable performance in classification of common birds such as the American Crow and the California Gull. Moreover, it can also distinguish some nuances between distinct species of birds and distinguish the bird from the background environment.

Keywords: Computer Science, Machine Learning, Neural Network, Convolutional Neural Network, Image Classification, Image Identification, Bird, Birding, Ornithology

INTRODUCTION

During the long journey of species evolution, birds have played a significant role in ecosystems throughout the world. They can also be a significant indicator of habitat health and species richness (Niemi, Hanowski, Lima, Nicholls, & Weilland, 1997). Understanding the differences between different bird species also allows biologists to understand the evolutionary process and the mysteries of life. Ornithology, the study of birds, is popular among many people, partly because non-professionals can also play a significant role, such as observing, recording, and identifying birds (Encyclopedia Britannica, Inc., 2018; Storer, Gill, & Rand, 2018). Anthropogenic factors, including pollution, diseases, and climate change, are posing a threat to many types of birds, such as endangered birds of prey (Azzarello & Van Vleet, 1987; Crick, 2004; Tella, 2001).

As concerns for environmental conservation grow, it is increasingly necessary to identify species for environmental conservation purposes. Identification of birds has been a problem for ornithologists, birders, biologists, and environmentalists alike. The main challenge of bird identification is the sheer variety of bird taxonomy and the nuanced differences between species. This presents a formidable challenge for many, which can be solved with various machine learning algorithms, including convolutional neural networks, a type of algorithm that excels in extracting features from images and classifying them into categories, which will be the focus of this paper. In recent years, machine learning has emerged as a new technique for various tasks, including image classification. This research will attempt to solve a bird identification problem based on images using machine learning techniques.

Previous research on this topic has used machine learning. For example, one previous research by Allison M. Horst, Alison Presmanes Hill, and Kristen B. Gorman aimed to classify three different penguin species based on data collected from Palmer Archipelago islands. However, the classes were limited to Gentoo, Chinstrap, and Adelie penguins. The dataset was textual instead of image. (Horst, Hill & Gorman, 2022).

This research project is an attempt to improve upon previous research. There are 10 different bird species the model will classify.

1. American crow (Corvus brachyrhynchos): A highly intelligent and social bird found in most parts of the US that feeds on a variety of food sources, from berries to little birds. They often work together for food and are active in many rural and urban areas (Montgomery, 2023).

2. Blue Jay (Cyanocitta cristata): This species is found to the east of the Rockies, with a perky crest and blue plumage. They often feed on nuts and insects, and often harvest acorns and hoard them in the ground (National Audubon Society, 2023).

3. Vermillion flycatcher (Pyrocephalus rubinus): as its name suggests, this is a subtype of the tyrant flycatchers in which males typically show a bright red color. They feed on insects by catching them while in flight in a behavior known as flycatching (National Audubon Society, 2023).

4. Western Grebe (Aechmophorus occidentalis): a type of waterfowl that is found in western US and Mexico. It is signified by its red eyes, red beak, and is well known for its unique mating dance in which the male and female “run across” the

surface of the water (Cornell Lab of Ornithology, 2023).

5. Yellow Warbler (Setophaga petechia): a subtype of the wood warbler family, the yellow warbler is signified by its mostly yellow plumage, with a few stripes of chestnut color on the breast for males and overall yellow for females (Cornell Lab of Ornithology, 2023).

6. Cactus wren (Campylorhynchus brunneicapillus): A type of wren found in North American desert environments, from southwestern US to Mexico, signified by deep brown spots throughout its body. Its population is facing a decline due to rapid urbanization destroying its habitat (Cornell Lab of Ornithology, 2023).

7. Indigo Bunting (Passerina cyanea): A type of songbird found throughout eastern North America. Breeding males are signified by a bright blue color and females are signified by a brownish color. It is worth noting that non-breeding males have a blue and brown plumage. For identification purposes, the indigo buntings in this dataset are all breeding males (National Audubon Society, 2023).

8. Eastern Towhee (Pipilo erythrophthalmus): an eastern songbird that is relative to spotted towhee found throughout the west. Males have black back, rufous sides, and white belly, while females have brown back, rufous sides and white belly (Cornell Lab of Ornithology, 2023).

9. California Gull (Larus californicus): a type of seagull found through the western US and Mexico. Not to be confused with Herring gulls or Western gulls since they have yellow legs instead of pink and have dark eyes (National Audubon Society, 2023).

10. Ruby Throated Hummingbird (Archilochus colubris): The only hummingbird species that is found east of the Great Plains. They are excellent flyers and can flap their wings more than 50 times per second (National Audubon Society, 2023).

METHOD

Data Source

The source of the data used in this project is Caltech-UCSD birds 200, which contains images of 11788 images of 200 common bird species in North America taken in 2011 (Caltech, 2011).

Data Preprocessing

For the sake of simplicity, we decided to limit the classification categories to 10 instead of 200. Each bird category consists of 60 different images. To increase the size of the dataset, we augmented the number of images in each category to 120 by flipping each image sideways. This is because the original data sample is too small to perform adequately, and the new data sample had a significant improvement. However, we realized that there is still room for improvement for data diversity. As a result, we further augmented the number of images in each category to 240 by flipping each image upside down, which improved the performance even more. The training and test dataset are split with the ratio of 80:20 ratio, respectively. The random state is set to an arbitrary seed 100 to ensure that the train set and test set are consistently split. The training set is used to train the data, and the test set is used to evaluate the same model's accuracy in another random sample.

Models Used

This project utilizes the Convolutional Neural Network. Convolutional Neural Networks are a type of computational algorithm that has a similar structure to interconnected human neurons. The neural network consists of multiple layers, each layer filled with a certain number of nodes. Each node has a unique activation function and parameter associated with it. The neural network algorithm aims to find the optimal value of parameters that minimizes the loss function, which is a measure of error of the classification of the test set (A. Ilesanmi & T. Ilesanmi, 2021). Convolutional Neural networks consist of two types of layers: convolutional and dense, the former used to process 2d images, and the latter used to process 1d tensors after flattening (Mishra, 2020).

The Structure of the Model

The final version of the Convolutional Neural Network uses the Adam optimizer, the categorical cross entropy loss function, and consists of:

- One input layer
- One convolutional layer with the activation “ReLU”
- One 2d pooling layer
- One flattening layer
- Two Dense layers with ReLU as the activation function
- One output Dense layer with 10 nodes and softmax as the activation function

RESULTS

Tables 1 to 8 below show the metrics of each version of the model using holdout validation. The eighth model performed the best. The metrics of each version improved from the previous one. The validation accuracy of the best-performing model (i.e. the eighth) was 75%. The macro average recall and the macro average F1-score was 75% as well, while the macro average precision was 76%.

Overall, the bird species that was the most accurately identified was #3(Western Grebe). This is likely because of its unique shape as a member of the order Podicipediformes. Bird #0(American Crow), #2(Vermilion Flycatcher), and #4(Yellow Warbler) also were well-identified, likely because of their distinctive color. Though the performance was impressive, the model was more mediocre in identifying birds #1(blue jay) and #7(eastern towhee). This is likely because of these species’ mixed colors, causing the model to confuse them with similar-looking species, such as confusing blue jays with indigo buntings.

The first version of the model, i.e., Version 1, consists of 1 convolutional layer without applying an activation function. It also includes 1 flattening layer, and 1 output layer. Table 1 below shows the performance of version 1.

Table 1

Classification Report of Version 1

	Precision	Recall	F1-Score
American Crow	0.33	0.33	0.33
Blue Jay	0.23	0.31	0.26
Vermilion Flycatcher	0.95	0.95	0.95
Western Grebe	0.60	0.09	0.16
Yellow Warbler	0.50	0.32	0.39
Cactus Wren	0.12	0.50	0.19

Indigo Bunting	0.29	0.50	0.37
Eastern Towhee	0.00	0.00	0.00
California Gull	0.71	0.18	0.29
Ruby-Throated Hummingbird	0.57	0.38	0.46
Micro Average	0.33	0.33	0.33
Macro Average	0.43	0.36	0.34
Weighted Average	0.44	0.33	0.32
Samples Average	0.33	0.33	0.33

For version 2, an activation function of ReLU was added to the convolutional layer in the model. Table 2 below shows the performance of version 2.

Table 2

Classification Report of Model 2

	Precision	Recall	F1-Score
American Crow	0.74	0.83	0.78
Blue Jay	0.39	0.38	0.39
Vermilion Flycatcher	0.95	0.95	0.95
Western Grebe	0.67	0.69	0.68
Yellow Warbler	0.90	0.86	0.88
Cactus Wren	0.44	0.50	0.47
Indigo Bunting	0.56	0.62	0.59
Eastern Towhee	0.62	0.21	0.31
California Gull	0.51	0.64	0.57
Ruby-Throated Hummingbird	0.61	0.67	0.64
Micro Average	0.63	0.63	0.63
Macro Average	0.64	0.64	0.63
Weighted Average	0.63	0.63	0.62
Samples Average	0.63	0.63	0.63

For version 3, a dense layer with no activation function before the output layer was added. Table 3 below shows the performance of model version 3.

Table 3

Classification Report of Version 3

	Precision	Recall	F1-Score
American Crow	0.86	0.79	0.83
Blue Jay	0.53	0.34	0.42
Vermilion Flycatcher	1.00	1.00	1.00
Western Grebe	0.68	0.72	0.70
Yellow Warbler	0.95	0.82	0.88
Cactus Wren	0.26	0.31	0.20
Indigo Bunting	0.67	0.75	0.71
Eastern Towhee	0.48	0.42	0.44
California Gull	0.47	0.57	0.52
Ruby-Throated Hummingbird	0.60	0.71	0.65
Micro Average	0.64	0.64	0.64
Macro Average	0.65	0.64	0.64
Weighted Average	0.65	0.64	0.64

	Precision	Recall	F1-Score
Samples Average	0.64	0.64	0.64

For version 4, another dense layer with leaky ReLU as the activation function was added. Table 4 below shows the performance of model version 4.

Table 4

Classification Report of Version 4

	Precision	Recall	F1-Score
American Crow	0.79	0.79	0.79
Blue Jay	0.67	0.34	0.45
Vermilion Flycatcher	0.87	1.00	0.93
Western Grebe	0.85	0.69	0.76
Yellow Warbler	1.00	0.77	0.87
Cactus Wren	0.56	0.62	0.59
Indigo Bunting	0.52	0.71	0.60
Eastern Towhee	0.61	0.46	0.52
California Gull	0.55	0.79	0.65
Ruby-Throated Hummingbird	0.69	0.86	0.77
Micro Average	0.69	0.69	0.69
Macro Average	0.71	0.70	0.69
Weighted Average	0.71	0.69	0.69
Samples Average	0.69	0.69	0.69

For version 5, another dense layer with leaky ReLU as the activation function was added to the model. Table 5 below shows the performance of model version 5.

Table 5

Classification Report of Version 5

	Precision	Recall	F1-Score
American Crow	0.78	0.75	0.77
Blue Jay	0.63	0.41	0.50
Vermilion Flycatcher	0.78	0.90	0.84
Western Grebe	0.85	0.88	0.86
Yellow Warbler	0.94	0.77	0.85
Cactus Wren	0.61	0.69	0.65
Indigo Bunting	0.58	0.75	0.65
Eastern Towhee	0.47	0.33	0.39
California Gull	0.61	0.79	0.69
Ruby-Throated Hummingbird	0.73	0.76	0.74
Micro Average	0.70	0.70	0.70
Macro Average	0.70	0.70	0.69
Weighted Average	0.70	0.70	0.69
Samples Average	0.70	0.70	0.70

Although version 5 was already achieving impressive performance, we realized that the data diversity in the original sample can still be improved. Thus, we augmented the data sample once more by flipping each image upside down, so each bird now has 240 images. Table 6 below shows the performance of model version 6.

Table 6

Classification Report of Version 6

	Precision	Recall	F1-Score
American Crow	0.77	0.85	0.81
Blue Jay	0.70	0.40	0.51
Vermilion Flycatcher	0.84	0.76	0.80
Western Grebe	0.77	0.85	0.81
Yellow Warbler	0.87	0.76	0.81
Cactus Wren	0.48	0.73	0.58
Indigo Bunting	0.59	0.80	0.68
Eastern Towhee	0.42	0.27	0.33
California Gull	0.45	0.60	0.51
Ruby-Throated Hummingbird	0.75	0.65	0.70
Micro Average	0.67	0.67	0.67
Macro Average	0.67	0.67	0.65
Weighted Average	0.68	0.67	0.66
Samples Average	0.67	0.67	0.67

After augmenting the image data once more, we realized that the performance fell a bit. To adjust for this change in version 7, we made a few adjustments to version 6, including adjusting the pooling layer's filter size and changing the first dense layer's activation function to ReLU. This improved the performance significantly. Table 7 below shows the performance of model version 7.

Table 7

Classification Report of Version 7

	Precision	Recall	F1-Score
American Crow	0.79	0.88	0.83
Blue Jay	0.66	0.56	0.61
Vermilion Flycatcher	0.91	0.74	0.82
Western Grebe	0.81	0.83	0.82
Yellow Warbler	0.88	0.83	0.86
Cactus Wren	0.46	0.79	0.58
Indigo Bunting	0.69	0.85	0.76
Eastern Towhee	0.65	0.49	0.56
California Gull	0.63	0.70	0.67
Ruby-Throated Hummingbird	0.82	0.60	0.69
Micro Average	0.73	0.73	0.73
Macro Average	0.73	0.73	0.72
Weighted Average	0.74	0.73	0.73
Samples Average	0.73	0.73	0.73

For version 8, the final and best performing version so far, we made some final adjustments to further improve the model's performance, such as adjusting the number of nodes and adding another dense layer with ReLU as the activation function. Table 8 below shows the performance of model version 8.

Table 8

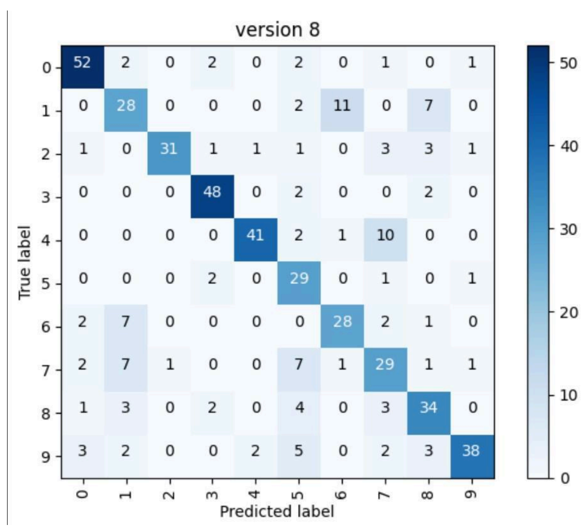
Classification Report of Version 8

	Precision	Recall	F1-Score
American Crow	0.85	0.87	0.86
Blue Jay	0.57	0.58	0.58
Vermilion Flycatcher	0.97	0.74	0.84
Western Grebe	0.87	0.92	0.90
Yellow Warbler	0.93	0.76	0.84
Cactus Wren	0.54	0.88	0.67
Indigo Bunting	0.68	0.70	0.69
Eastern Towhee	0.57	0.59	0.58
California Gull	0.67	0.72	0.69
Ruby-Throated Hummingbird	0.90	0.69	0.78
Micro Average	0.75	0.75	0.75
Macro Average	0.76	0.75	0.75
Weighted Average	0.77	0.75	0.75
Samples Average	0.75	0.75	0.75

Another way to visualize the performance of the models is through a confusion matrix, with the grids symbolizing the true label and predicted label of an image. The ideal performance would align on the diagonal from the top-left corner to the bottom-right corner, symbolizing that the true labels and the predicted labels match each other. The confusion matrix below represents the model with the best performance, which is version 8. As shown in Figure 1 below, the model had a great performance most of the times, especially when identifying birds assigned the true labels #0(American Crow), #2(Vermilion Flycatcher), #3(Western Grebe), and #4(Yellow Warbler), achieving a robust F1-Score of 0.86, 0.84, 0.90 and 0.84, respectively. While the model can often identify birds assigned the true labels #1 (blue jay) and #7 (eastern towhee), the performance is more mediocre when compared to the other types of birds. This can be explained because it is possible to confuse these birds with other species that look similar, such as confusing #1(Blue Jay) with #6(Indigo Bunting) because they both have blue in their colors, and confusing #7(Eastern Towhee) with #8(California Gull) because they both have white in their colors.

Figure 1

Confusion Matrix of Model Version 8

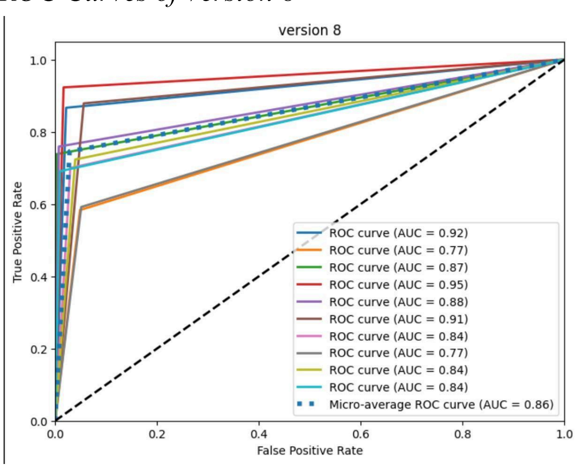


Another visualization method is to use a Receiver Operating Characteristic (ROC) curve, which is a graph of the true positive rate (TPR) as a function of the false positive rate (FPR) in the domain and range of [0,1]. The TPR, which is high in ideal cases, is calculated as (True positive) / (True Positives + False Negatives), and the FPR, which is low in ideal cases is measured as (False Positives) / (False Positives + True Negatives). This means that in ideal cases, the curve would be as close to the top left corner as possible, signifying that there are only true positives and no false positives. A method to measure how accurate the model performs is looking at the area under the curve (AUC) of an ROC curve. Models that have better performance have an AUC closer to 1.

Figure 2 below shows the ROC curve of version 8. The black line is the diagonal of the graph, representing the curve if the decision is made entirely randomly. As shown in Figure 2, all curves are far away from the diagonal and close to the top-left corner, meaning that they performed fairly well. The model performs exceptionally well at identifying American Crow (represented by the dark blue curve) and Western Grebe (represented by the red curve), achieving an exceptional AUC of 0.92 and 0.95, respectively. The ROC curve of Blue Jay (represented by the orange curve) and Eastern Towhee (represented by the grey curve) are close to the black diagonal, meaning that they performed relatively mediocre compared to the others.

Figure 2

ROC Curves of Version 8



DISCUSSION

When the model makes random guesses, predicted accuracy is 10%. After many adjustments to the model, the accuracy increased to 75%, which is a substantial increase in performance. This increase in accuracy illustrates that it is a reliable method to classify the images in the dataset. Though initially we faced some limitations, we managed to tackle them all through a variety of methods.

When initially processing the data, we faced some limitations, such as data diversity. However, we addressed it through data augmentation: artificially increasing the data amount without adding new data into the dataset, which is often done when data is not readily available (Chlap, Min, Vandenberg, Dowling, Holloway, & Haworth, 2021). We managed to address this problem through data augmentation by flipping the image sideways and appending them to the data files. This significantly increased accuracy. However, after revising the data we realized that there is still room for improvement, so we augmented the dataset once more by flipping all the images upside down, significantly increasing the data size to 4 times the original size. As shown in figure 3, 4, and 5 below, there is a visible increase in performance of the model each time the data gets augmented as the ROC curves shift towards the top-left corner, meaning a higher TPR and a lower FPR.

Figure 3

ROC Curves of Version 8 Before Image Augmentation

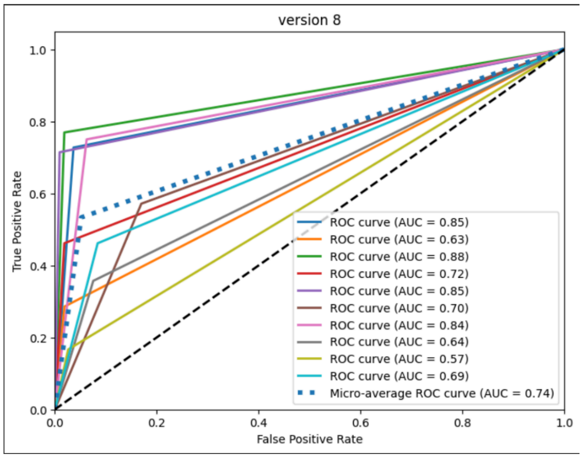


Figure 4

ROC Curves of Version 8 after Augmenting the Dataset to Twice its Original Size

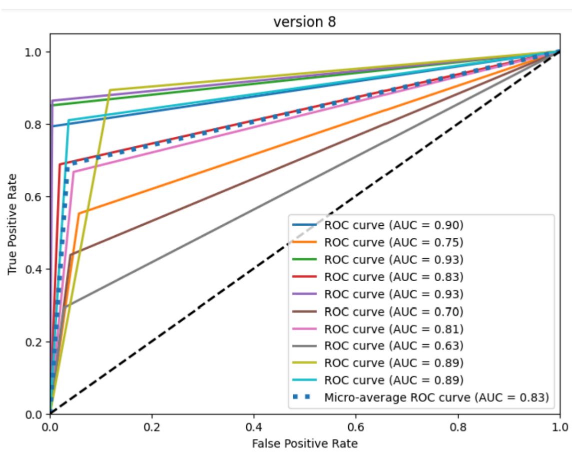
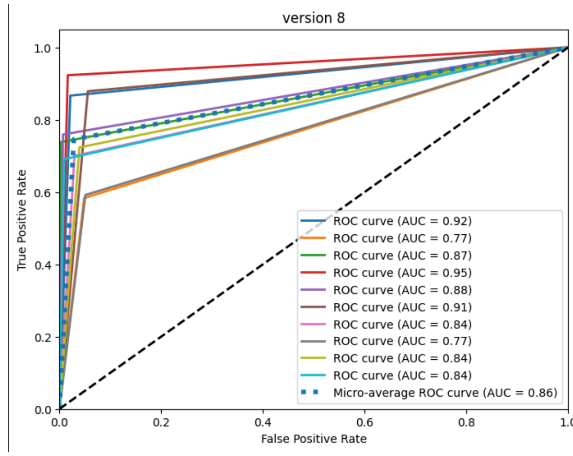


Figure 5

ROC Curves of version 8 after augmenting the dataset to four times its original size



Another limitation is the hardware requirements. To train the data, large storage is required. The most developed layout of seven layers has shown to take a large amount of computing resources. However, we also managed to tackle this problem by using Google Colaboratory. Shifting the project online allows us to utilize Google Colaboratory's high computing power, allowing us to build a more robust model without worrying about the program crashing.

CONCLUSION

This research project aims to develop a convolutional neural network that serves as an efficient way to classify birds based on its images. Based on further research, it can be concluded that convolutional neural networks have potential in achieving impressive results, and they can also adapt to handle the complexities inherent in bird image classification. In conclusion, the model did a decent job in classifying 10 common bird species, with accuracy at 0.75, macro average precision at 0.76, and macro average recall at 0.75 with 50 training epochs and an 80:20 train test split. This is significant since it is a potential direction where future improvements can be conducted such that the model will be able to identify a wider range of birds (with some tweaking and providing enough data) so it can serve as an alternative to human powered identification. This can potentially bring a new perspective in ornithology and help amateur birders better understand different bird species. Convolutional neural networks can revolutionize the field of avian identification, offering a cutting-edge solution that not only showcases its prowess in recognizing a diverse range of bird species.

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Is Health Insurance Health Assurance? An Investigation into the Effects of Step Therapy

By Xinchun Audrey Zhang

AUTHOR BIO

Audrey Zhang is currently a senior in the piano conservatory at Orange County School of the Arts (OCSA) in California. She hopes to become a physician that can provide both physically and culturally competent care in the future. She is passionate about bringing STEM education to the youth as the co-founder of Orange County Advanced Science Tutoring (OCAST), a nonprofit STEM tutoring organization for students in grades 4-8th, and project leader of EpiSTEMic, an effort aimed to increase interest in the sciences in underprivileged students of her local Orange community. In her free time, Audrey likes to crochet and explore different genres of music.

ABSTRACT

This paper explores Step Therapy (ST) in the U.S. healthcare system, an insurance policy requiring patients to try specific medications before accessing potentially more effective, costlier treatments. It discusses how this approach, aimed at cost control, affects patient care and physician-patient relationships, highlighting concerns about limited access to necessary medications and health complications. The work essentially emphasizes the need to understand step therapy's pros and cons that can inform potential legislative changes addressing its unintended effects.

THE ROLE OF STEP THERAPY IN HEALTHCARE

The essence of ST, or step edits, boils down to its aims of curbing costs on expensive drugs. As a type of insurance protocol, it does this by requiring patients to try a less expensive, often generic, alternative treatment before coverage of a more expensive treatment is authorized. Step therapy is used by both public and major private insurers to curb costs for expensive drugs, and its presence continues to rise in health care: in an analysis led by researchers at Tufts University, step therapy protocols were tracked across 17 insurers, and over 38.9% of coverage policies deployed step edit protocols (Lenahan et al., 2021).

There are multiple facets of rationale behind its popular implementation. One of the main reasons it is especially valued in the US healthcare system is because of the absence of negotiation for better prices with drug manufacturers. Unlike other countries, who negotiate drug prices by threatening non-coverage and subsequently the threat of discouraging consumer demand, the system in the US gives complete control over drug prices to the manufacturers. Insurers are only required to cover a select few "medically necessary" therapies, which lead to higher out-of-pocket tolls for patients using uncovered drugs.

For insurance companies, ST is designed as a tool for negotiating pricing; it is one of the few ways to help keep pharmaceutical prices in check. Insurance companies tier drugs in a formulary, or preferred drug list, where preferred drugs (often generics) are placed on lower tiers and require less patient monetary contribution relative to more expensive therapies, which are tiered higher (What is step therapy?, 2023). By requiring patients to use a less expensive formulation of a common drug before trying newer or more expensive versions, ST reduces demand for the higher tier drugs and helps patients and their insurers avoid exploitation by pharmaceutical companies (Hirch, 2018).

Another aspect of ST's popular implementation is the consideration for care quality. In other words, what drugs will be most effective for a patient after taking into consideration economical burden? The responsibility to practice cost-effective treatment has been a more recent phenomenon; this duty was only incorporated in the ACP Ethics Manual starting 2012, in its 6th edition. The most recent edition (the 7th) of the ACP Ethics Manual has revised policies for cost effective treatment, specifically stating that insurance companies may take into account the cost-effectiveness of different treatments (Santoro, 2019). In this regard, both doctors and insurers follow the same ethical mandate to make treatment plan decisions keeping both scientific knowledge and cost-effectiveness in mind—which is why there is an extensive, integrated patient care process in the prescription of drugs, referred to as formulary management. Its primary purpose is to encourage the use of affordable and beneficial medications, and it is supported by evidence-based medicine as well the experience of experts in the field (AMCP, n.d.). A big part of formulary management is to carefully apply step therapy protocols when necessary, in order to maintain a standard of patient care without ethically imposing on a patient's financial status.

When considering the step edit implementation as a whole, it is important to note a fine line between patient and insurer benefit from step therapy in terms of a monetary perspective. While it is true that step therapy was designed to control costs of drugs, its implementation does not necessarily mean

savings for the patient. For example, insurance companies can use step therapy as an intervention to reduce accessibility to expensive drugs, at the sole benefit of the insurer.
Having provided a substantial background on the reasoning behind the practice, the following sections of the paper will investigate the various effects of step therapy, often in a clinical setting, in detail.

THE ADVANTAGES OF STEP THERAPY

As per its original purpose, step therapy is an effective and popular way to cut costs on drugs for drugs. In a study of fourteen evaluations of step therapy programs over five therapy classes — antidepressants, antihypertensives, antipsychotics, nonsteroidal anti-inflammatory drugs (NSAIDs), and proton pump inhibitors (PPIs)—the research demonstrated consistent and statistically significant drug cost savings for all drug classes except for the antipsychotics (Motheral, 2011). Additionally, the five studies that were examined for effects of step therapy on higher disease-related spending found no statistically significant higher outpatient expenditures. The study supported the idea of significant drug savings through ST programs, through greater use of lower-cost medications.

In a separate study, step therapy programs were deployed in the workplace. For reference, employers with 50+ full-time employees are required to provide health insurance to 95% of their full-time employees under the ACA Rules on Employer-Sponsored Health Insurance (Sachi, 2023). This study was designed to examine ST's effect on plan-sponsor savings. For a decrease of 0.83 dollars per-member-per-month in net cost after implementing step therapy, the program produced significant drug savings (Motheral, 2011). It acknowledged the idea that, with step therapy, healthcare can be easier to afford and properly implement within the workplace.

Step therapy programs have also risen in application outside of commercial businesses: formulary management of Medicare Part B for Medicare Advantage plans recently changed to implement ST programs. This implementation of ST in Medicare Advantage lowered costs and improved the quality of care for Medicare beneficiaries (Federal Register, 2018). Previous Centers for Medicare & Medicaid Services (CMS) guidelines prohibited step therapy; consequently, Medicare Advantage plans were not very successful in negotiating better value therapies for patients. By overruling this decision, the new negotiations helped decrease Average Sales Price for Part B drugs, and helped decrease copayments (CMS, 2018). Overall, step therapy programs have been strongly supported in managing cost efficiency for treatments, contributing to their recognition in various forms of US healthcare.

THE DISADVANTAGES OF STEP THERAPY

Despite its main purpose, there have been studies that show that step therapy can actually create more economic burden than relief. When patients are forced to follow step therapy protocols, they can undergo rounds of various medications before they receive a successful treatment, which is largely unnecessary for the patients with certain diseases that tend to do better with the more expensive medications (Mott, 2022). Patients then pay for several medications that are not the most effective for their condition, leading to higher out-of-pocket expenses. With multiple trials of treatment, the economic burden of step therapy becomes evident; extra trials result in delays in receiving the necessary treatments, excess medications, and a prolonged disease duration that all contribute to increased medical costs (Mott, 2022). In some cases, patients may not be able to afford the additional medications and decide to forgo treatment altogether to avoid the costs, which is neither beneficial to the patient in the short-term or long-term.

Some general ST medications can actually cause side effects and adverse reactions when medications that are not appropriate for specific patient conditions are applied. Similarly, this will not only increase payments for patients to address the new complications, but calls attention to the ethics of step therapy in regards to protecting patient health. Cases like these highlight the need for insurance policies to consider the medical needs of patients.

As a comparison point for the quality of clinical decisions, Clinical Practice Guidelines (CPGs) are generally considered the standard (Woolf et al., 1999). CPGs are made by authoritative physician groups to incorporate competing demands of evidence-based and cost-effective medicine (Santoro, 2019). However, the potential for physician specialty bias allows insurers the control over how much of ST policies would mirror CPGs (Santoro, 2019). This is why, in a study conducted at Tufts Medical Center, there were less than half of cases (34.1%) where ST protocols matched clinical guidelines (Zimmerman, 2023). Additionally, more than half of cases (55.6%) applied ST protocols that were more stringent than clinical guidelines (Minemyer, 2021). Insurers reprioritize costs in instances where CPGs' policies may result in decrease in cost effectiveness.

Furthermore, this becomes a major issue when different insurers create different step therapy policies based on their own reasoning and priorities. There is dramatic variation between plans (nearly 40% as indicated in one study), even for the same condition (Zimmerman, 2023); this can make moving insurers and/or changing plans disruptive for a patient who has tried one or more step therapies. Most often, inconsistencies across plans means a loss of eligibility for a therapy under the new plan and requirements of completing the new plan's step therapy protocol to regain access (Minemyer, 2021). In these cases, patients may need to connect with their physician and get prior authorization, or a step therapy exception, to continue coverage for an efficient drug therapy. However, with any exception approval process, physicians waste valuable time that could be otherwise allocated to direct patient care.

This brings into perspective the most serious of the flaws of step therapy—disruption to patient care. Its policies can be contradictory to those of a more knowledgeable healthcare provider. In other words, step therapy often requires patients to go through a series of treatment failures before gaining access to the medication that their healthcare provider believes to be the most effective and appropriate for their condition. There have been multiple cases in which step therapy strategies have no supporting clinical evidence or patient outcomes. For example, in the consideration of some anti-TNFs, a category of anti-inflammatory drugs used to treat rheumatoid arthritis, policies required specific drugs to fail before the tried-and-proven vedolizumab or ustekinumab (Bhat et al., 2017). There were no clinical studies that indicated that other anti-inflammatory drugs needed to be tried and proved unsuccessful before considering anti-TNFs. This resulted in delays in receiving optimal treatment—leading to prolonged suffering, disease progression, and increased healthcare costs (Bhat et al., 2017). Likewise, In a study of patients with psoriatic arthritis, patients under step therapy restrictions had 25% lower odds of treatment effectiveness.

Additionally, significantly more patients filled prescriptions for anti-inflammatory drugs, which is an indication of poorly managed disease; implying that there is a need to better align step therapy protocols with clinical practice guidelines published by medical professionals (Boytsov et al., 2019). For certain step edits, such as those for psoriasis, protocols were more stringent than clinical treatment guidelines over 95% of the time (Lenahan et al., 2021). For those with rare diseases, insurance policies often do not consider the unique needs and circumstances of individual patients and further alienates patients from the medical expertise and clinical judgment of healthcare providers. These patients more often than not require expensive, uncommonly used medications to treat their specific conditions, and the nature of step therapy can delay their access to the necessary treatments. For cancer specifically, the individualized nature of modern cancer treatment becomes especially incompatible with ST protocols (Santoro, 2019). Chris Hansen, president of the American Cancer Society Cancer Action Network, stresses dissatisfaction with the extra hurdles step therapy can create, as patients are forced to try multiple therapies before accessing the one initially prescribed by their doctor; patients who are living with chronic illness are subject to relatively more severe complications when health plan preferred medications are ineffective (Santoro, 2019).

When insurance policies are medically uninformed, relying solely on cost considerations rather than evidence-based medicine or personalized treatment plans, the options and autonomy of doctors in making the best decisions for their patients' health become limited. Switching medications or undergoing unnecessary treatment changes due to insurance requirements can further disrupt the patient-provider relationship as it can lead to confusion, frustration, and reduced trust of the patient in the healthcare system (Hagland, 2006). It is crucial for health insurance policies to carefully consider the medical appropriateness and patient-centeredness of step therapy protocols to minimize disruptions to patient care and ensure that treatment decisions are based on sound medical principles.

Last but not least, step therapy can be discriminatory against certain demographics. Demographic differences in step therapy can arise from geographic variation: protocols can vary greatly by state, with some states having more lenient policies and others having more restrictive policies. This can create a situation where patients with the same condition living in different states may have vastly different experiences accessing drugs with the same effectiveness. Different US states have different step therapy policies—some are based more strictly on medical criteria and expert guidelines and have a framework for exempting patients from step therapy if needed, but not all (NORD, 2023).

CONCLUSION AND IMPROVEMENTS ON STEP THERAPY

While there are both benefits and pitfalls of implementing step therapy, it is unique to the expensive US healthcare system. It can curve costs, but it can also be restrictive in access based on ability of pay and disruptive in the relationship between patients and physicians. These findings have strongly suggested and incited action for state and federal legislative initiatives to help ensure appropriate prescription drug use. Policy-makers and insurance companies are currently considering these disparities and are working towards creating more equitable and accessible healthcare for all individuals, regardless of their socioeconomic status or geographic location (Bhat et al., 2017). By doing so, they are helping to ensure that step therapy protocols are used appropriately and not as a barrier to the necessary and effective healthcare.

As of January 2023, 30% of states have yet to enact step therapy protection laws. However, a majority of states have, and the success at the state level has led to increased pressure on federal support. Proposed federal legislation, with bipartisan support, called the Safe Step Act would create more transparency about ST plans and would cover more patients—especially for those employed with health insurance plans (Zimmerman, 2023). This act will make amends to the Employee Retirement Income Security Act (ERISA), where it will require group health plans to provide an exception process for any medication step therapy protocol. It establishes a clear exemption process, and outlines five exceptions, which include issues addressed in section 3 of this review. These five exceptions are: 1. Failure of the required drug, 2. Delayed treatment, 3. A contraindication of the required drug, 4. Prevention of participation of their Activities of Daily Living (ADLs), and 5. Stability on their current medication (Step Therapy, 2022). Legislation like this would make the exception process for patients and physicians more efficient. By continually refining ST protocols while considering patient perspectives, the balance between cost containment and patient-centered care will continue to improve; ensuring that treatment decisions are based on both the best available evidence and individual patient needs.

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Neurobiological Foundation for Psychological Motivation Theories

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AUTHOR BIO

I'm Tatiana Lermusiaux, and I am a 17 year old high school student. I am interested in science, in particular the fields of neuroscience and psychology. I plan to major in one of those fields or another science field. I like learning new things and learning about new discoveries.

ABSTRACT

Psychological theories of motivation to date are rudimentary in that they assign the underlying explanatory component of motivation to either a single set of needs or to more cognitive influences like expectations or fairness. A review of the neurological processes taking place in motivated behaviors shows a much more complex and personalized situation. New distinctions are needed, for instance between wanting and liking, as it has been shown that wanting is a separate neural process from liking. Furthermore, neural patterns of learned dislike can be overridden by physiological imbalance that motivate new behaviors. In this review we propose that there is no grand theory of motivation that can address all individuals equally. We can, however, single out generic underlying theories, like incentive salience theory, that underlie the biological dopamine process for cue-based personal incentives. When applied to situations that require changes in motivation, such as interventions to stop a particular behavior, the current use of oversimplified theories of motivation hinder success. Therefore, this review highlights that attempting to alter a person's behavior and motivation, especially through an intervention requires unique, personalized strategies that go beyond broad-stroke psychological theories.

INTRODUCTION

Psychological motivation theories are useful for categorizing, understanding, and influencing behaviors. Those theories are often based on observational studies or questionnaire-based inquiries. Consequently, they are seen by neuroscientists as categories with no real connection to the true underlying biology or physiology. In this review, we aim to draw connections between categorizations and neurobiology (Figure 1.). This is part of a larger movement within the National Institute of Mental Health (NIMH) called Research Domain Criteria (RDoC), which has stated an explicit goal of integrating many levels of information, including genomics, circuits, physiology, and behavior, to better understand the basic dimensions of functioning underlying the full range of human behavior. (Pacheco, 2022) Our review aims to revisit the categorizations of psychological theories and promote the ones that are the closest to their neurobiological foundation. Several levels of connections have been suggested years ago (Insel, 2010), ranging from the self-reports to observed behaviors, neural circuitry, molecular mechanisms, and finally to genetics. In this paper, we will only make the jump to the psychological theories of motivation which are historically based on self-reports and behaviors, and go to the circuits level.

The overarching purpose of this review is to promote theories that better tie motivational theories to their neurobiological foundation such that more effective behavioral interventions can be developed. This work relates to other fields, such as the diagnostics of ADHD, autism or childhood irritability, in that they also have sub-types and require complex, individualized treatments (Pacheco, 2022).

DEFINING MOTIVATION

To be understood, motivation implies a goal. A goal is sought to gain a desired state (Bong, 2023) (see Figure 2). We're always motivated to achieve something. There is no motivation created without a desired goal. However, the biology behind motivation is more difficult to define. The neurobiology of motivation requires a neuroscientist to understand the neural processes stimulating selective behaviors that drive someone toward a larger goal. In other terms, motivation is the precursor of behaviors toward what people want and what they decide to do.

But where do goals come from? At the origin, any goal is rooted in needs.(Bong, 2023) Those can be physiological needs (thirst, hunger) or psychological needs (relatedness, competence, predictability). As those needs ask to be fulfilled, they trigger a state that motivates a goal as a way to reach the state. The mental processes that combine goal selection and triggered action is what we call motivation.

In its basic form, we may want to walk to a fountain (action) to get water (goal) and not to be thirsty (state). We want to walk to a pub (action) to meet some friends (goal) to not be alone all evening (state avoidance). As you can judge from these two examples, distinct goals can intertwine, i.e. while drinking in the pub you also did not become thirsty. Very quickly through life's multiple dimensions, goals become more complex and move beyond a directly connected goal to an original single need. Moreover, the contextual learning process of each goal fulfillment creates a diversity of ways to satisfy our needs. For instance, we may decide to drink water, lemonade, or beer. They all will help to reduce thirst and will add as we will see other complexities to the motivational pathways. Similarly, beliefs, perceptions, and emotions influence the motivation process, adding many more layers to the complexity of motivated behaviors. For instance, if you believe sugar or alcohol is not good for your health, you may not eat candy or drink alcohol even when you are hungry or thirsty. The complexity of human culture and belief systems therefore influences the power of motivation. Another layer of complexity is that many of the motivational influences are not all conscious. In fact, the majority of the influences on our behaviors are non-conscious (Bong, 2023). This especially highlights the need for neurobiological analysis in understanding motivation, as a questionnaire-based approach would not be able to track unconscious decision making. Moreover, as individual strategies to fulfill certain needs are learned, patterns are formed and can be referred to as traits or personality. It is important to understand individualistic behavior patterns, or personality traits, when considering motivation and attempts to change behaviors. In summary, motivation is the combination of the selection of a goal and the action attached to it. The goal foundations can be considered as psychological needs. Identifying key neurobiological underpinnings of motivation and how it relates to these psychological needs will unlock the key to more easily changing people's behaviors.

PSYCHOLOGICAL THEORIES

Historically, motivation has been a concept used mainly in psychology and is rich in theories (Dean Mobbs, 2013). Maslow with its pyramid of needs is probably the most well known, but many other theories emerged over the years. Maslow created a pyramid of needs, he observed and learned from the people around him and created this pyramid based on what he thought was most important. The bottom of his pyramid starts with physiological needs (food, water, warmth, rest), then movies up to safety needs (security, safety), then belongingness and love needs (intimate relationships, friends), then esteem needs (prestige and feeling of accomplishment), and lastly self-actualization/self-fulfillment needs (achieving one's full potential, including creative activities.) At the bottom of the pyramid, he is stating things we need to survive, and as we go up the pyramid it's more mental and psychological things we need. McLelland had a concept about needs where he thought that everyone has driving motivators; achievement, power and affiliation, and implicit influence. Alderfer had a theory of need as well called ERG where he believed there were three leaves of needs: existence, relatedness, and growth. Skinner had a concept of reinforcement where he believed that the environment would create reinforcement and motivation actions. There's also the theory of Equity where the core concept is fairness or reinforcement. This theory says that the fairness of rewards will impact the role in which motivation happens. The theory of Expectancy has the concept of expectations. This concept says that motivation will depend on if there is a positive outcome. Lastly, the theory of self-determination is a concept of needs. This concept has three parts; competence, achievement, and autonomy. (see Table 1.)

Table 1. Psychological Core Concepts.

This table summarizes the core concepts of each psychology theory.

Theory Name	Year	Core concept	Explanation
Maslow	1954	Needs	Five core needs (physiological, safety, social, esteem, and self-actualization) push us to act to fulfill them

McLelland	1961	Needs	Achievement, power, and affiliation and their implicit influence.
ERG	1969	Needs	Three needs levels: existence, relatedness, and growth
Skinner	1954	Reinforcement	The environment creates reinforcement and motivates action
Equity	2001	Fairness or reinforcement	In the social environment, the fairness of rewards plays a major role in motivation
Expectancy	1964	Expectation	Motivation is dependent on the likelihood of a positive outcome.
Self-determination	1980	Needs	Three cores: Competence, achievement, and autonomy

We can categorize the motivation-independent variables into the following categories. (1) Need-based, linked to an internal innate requirement (similar to homeostasis). (2) Environment-based, linked to external reward and reinforcement, can be social. (3) Belief-based, linked to the internal creation of goals or expectation modulation.

We can summarize the third column showing there are only three independent variables influencing motivation. If we think of motivation as a function we can write it as we have done below and state that motivation is dependent on (1) the internal needs or unconscious motives of the individual. (2) The external rewards, and (3) the beliefs that have been learned. Hence we can summarize that any motivation theories we have reviewed are a function of those.

Motivation = f (needs, external reward, belief)

SIMPLIFIED BEHAVIORAL NEUROSCIENCE OVERVIEW OF MOTIVATION

Motivation as we have defined it is the energizing of behavior in pursuit of a goal. Existing behavioral neuroscience analysis converges with our categorization of the three independent variables of needs, external reward, and belief. Those three factors influence motivation of an organism's internal physiological states, the current environmental conditions, as well as the organism's history and experiences. Shown in Figure 3 adapted from Simpson and Balsam (2015), where the three factors enter into a cost/benefit calculation to compute motivation. While the cost/benefit analogy is shared by many (Bong, 2023), others suggest that the winning goals depend greatly on the strength of the mental representation influenced by internal and external stimuli. While Simpson and Balsam (2015) admit the limitation of our current understanding of the cost-benefit computation, having clarity of the input components driving motivation - even if the decision is made in a black box - can still help to impact its outcomes. A similar metaphor as the cost-benefit computation to understand the mind is the hedonic sharpener (Knutson & Srirangarajan, 2019) which is not precise but tries quickly to optimize pleasant feelings. However, we understand the complexity of the concept of motivation as it involves the processes of learning, perception, and physiological states. In summary, a simplified view of the motivational influences of any action can be represented by a prediction computation of cost and benefit coming from our internal physiology, the feedback of our environment via our sensors, and our beliefs. It is now time to see the underlying processes uncovered so far by neurobiology that influence those three inputs.

MOTIVATIONAL NEUROLOGICAL PATHWAYS

From Drive Theory to Incentive Salience Theory

Early theories in motivation started with the assumption that we were mostly driven to reduce our unpleasant physiological drives (such as hunger and thirst). Drinking water eliminated our unpleasant thirst drive. However, numerous analyses of the brain motivation circuitry (Berridge, 2018) shows that we are more incentive-driven than drive reduction-driven, even though the drive reduction seems intuitively appealing.

Our brain does not try to reinforce the motivation for us to seek or avoid a state, i.e. fulfill a lack of water, but our circuitry seems to be built to motivate the action of getting water. In other words, we are rewarding progress, not satiation. Many experiments have shown (Berridge, 2018) that thirst or hunger will enhance the incentive to act, but only if there is a way to act.

The theory that seems to better reflect the internal functioning of our brains is called the incentive salience theory of motivation. The incentive motivation is often divided into three types of mechanisms: wanting, liking, and learning (Berridge, 2018). Liking is anatomically located in scattered hedonic hotspots, going from the cortex to the brainstem. Wanting is associated with dopamine processes and is located in the Ventral Tegmental Area and the striatum. The relative robustness of the wanting circuitry compared to the liking circuitry seems to be an explanation for why high levels of dopamine give us a feeling of energy, engagement, and focus and reinforce the motivation to exert effort (Salamone, 2018), not just to enjoy pleasure. This sense of productivity or progress towards a worthwhile goal is what the mesolimbic dopamine pathway reinforces. Modern neuroscientists are increasingly confident that the main processes for motivated actions are not reinforced by drives but by learned wanting. This leads us to a critical distinction between wanting and liking.

Wanting vs. Liking

In our day-to-day life, we often equate wanting and liking. We assume that we would only want and be motivated to seek what we like. Research has shown that the wanting can vary dramatically while the liking may not have changed much (Berridge, 2016). Many experiments have confirmed that what drives motivation, or the fact of making an action towards a goal, is not the lack of liking, but the lack of wanting it. The question could be asked about the real role of the liking process if what matters for survival and reproduction is wanting. One of the most recognized figures in this field, Kent Berridge (2016), made the conjecture that liking could be there only for the original learning and some reinforcement. Our next question is to better understand motivation and what we came to understand as the core process: wanting.

Incentive salience vs. wanting

What we understand so far is that to understand motivation, wanting is the core of the focus as it is the source of the action. Wanting can have two forms; cognitive wanting is based on cognitive expectations and is goal-oriented, while incentive salience is often written as ‘wanting’, is a mesolimbic dopamine-related system, and is cue-triggered to obtain a reward

(Berridge, 2018). Typically wanting (cognitive expectation) and 'wanting' (incentive salience) are aligned and the 'wanting' linked to the dopamine system facilitates action.

'Wanting' will look for triggers in the world, they can be physical stimuli or in the imagination. For instance, if someone sees a bottle of cold water, it triggers them to go towards drinking it. Or imagine serving a glass of sparkling water. Both can act as triggers to want water. Even though our brain can learn new triggers, over time with repeated activation of a specific trigger, we can narrow our want to the extreme, and that can lead to addiction. We have seen in this section, that incentive salience or 'wanting' is a process linked to the dopamine system and triggering actions linked to cues. Those cues can be physical or imaginary.

Physiological influence on our 'wants'

The concept of Alliesthesia is the experience that we will enjoy a glass of water more if we are thirsty, food if we are hungry, and so on. The 'wanting' can adjust automatically with physiological needs changes. An experiment that models this exposing a rat to high salinity water. The rat initially shows dislike for this salty water, but when induced in a low sodium state it will spontaneously go towards the salty water lever without any new training or learning.

This begs the question of how a learned– dislike can be transformed without new learning to a desire for a particular cue or substance. This is where the incentive salience or 'wanting' of the mesolimbic process can complement the cortical cognitive system. We can see that physiology influences our wants. New research (Dohnalová, 2022) on mice also shows that the microbiome can influence the dopamine level in reaction to exercise, hence promoting athletic activities and performance.If those translate to humans, that would be another level of influence and a mind-body connection. In short, physiology can help trigger the 'wanting' but does not seem to reinforce the motivation, while, for instance, the microbiome can influence dopamine levels.

Learning and rewards

Some experiments have shown an increase or a decrease of dopamine based on expectations being fulfilled or not, which is referred to as the reward prediction error. This is because the mesolimbic dopamine pathway is involved in the anticipation of reward, rather than the experience of reward itself. When we are working towards a goal, the mesolimbic dopamine pathway is activated as we anticipate the reward that we will receive when we achieve the goal. However, the reward prediction error theory seems to be in some conflict with the incentive salience theory, which also claims a critical role for dopamine. However, experiments that distinguish between rapid changes in dopamine (phasic) versus slower changes in base level (tonic) reconcile the dopamine role in both learning and motivation (Wang, 2021). Beliefs influence greatly as well and modify the dopamine level, but mostly linked to learning when there is a quick change in dopamine levels.

Cognitive control and motivation

It is well accepted-that self-discipline can exert some control over our motivation. Those processes are typically linked to conscious cognitive control. For cognitive control, many regions of the prefrontal cortex are active (Kim, 2016). The amygdala is responsible for the evaluation and the signal back to the dopamine neurons, but the amygdala also receives signals from the prefrontal cortex.

Hence, we see that motivation happens to someone due to external influences, but also from internal prefrontal cortex influx. It is reasonable to expect that the prefrontal cortex influences what we perceive as our rational choices.

However, there are several observed influences in the decision-making process that are worth noting and linking backward from the rational to the dopamine process. (1) The dopamine hypothesis; the presence of a mild positive feeling will influence the cognitive process. The positive feeling increases dopamine, which in turn facilitates cognition. However, this only works as long as there is not an awareness of the positive influence. (2) Priming; the exposure to a stimulus outside the conscious awareness. A known example is the fact that it has been shown that the odor of cleaning products motivates cleaning actions. (3) The somatic marker hypothesis; the consolidation of how someone feels (introperception) with the actual task and social context.

In comparison, dopamine influences of the mesolimbic system on the prefrontal cortex exist and are typically called bottom-up influences. Other more top-down influences on cues are the cortical circuits acting as inhibitors and creating even more variations in those processes. We have seen here that the prefrontal cortex is also deeply involved in motivation.

Individual variation in motivational cues

One of the consequences of looking at the incentive salience theory as a foundation of motivational theory is the importance of cues. Cues, seen in the Pavlovian learning approach as conditional stimuli, can generate a conditional response, for example salivating in the well-known Pavlov experiment. However, conditional stimuli can become an incentive stimulus when connected to emotional and motivational states. We have seen that incentive stimuli are at the base of ‘wanting’ and the source of motivation. However, research has shown (Flagel & Robinson, 2017) considerable individual variation in how conditional stimuli act as an incentive stimulus. In other words, the cues that motivate someone for an action can be very different from what motivates someone else for the same action.

Consequently, we looped back to our original question of looking for neurobiological foundations for psychological theories. We are meant to believe that to have effective psychological theories for interventions, we will need to take into account the individual variation. The connection of incentive salience theory, or ‘wanting,’ introduces a level of individual variability. This shows the limit of the reliance on physiological processes to offer a foundation for psychological categories.

CONCLUSION

Finding a connection between motivational psychological theories and neurological and biological processes is very complex. There is still a lot of research being done to see if there could be a connection. Our findings highlighted that motivation processes rely on mesolimbic dopamine-dependent actions. Those actions are not reinforced by drive or liking but by cues triggered by ‘wanting’. While physiological needs can act as a trigger for action, relying only on them to create psychological motivation theories is not enough. The individuality of the cues created, and the influence of the cognitive control regions of the brain make us believe that any complete psychological motivational explanation cannot be restricted to simple categories. Further research will have to be done to continue to confirm the incentive salience theory as the best way to depict the internal processes of our motivated actions.

ANNEX

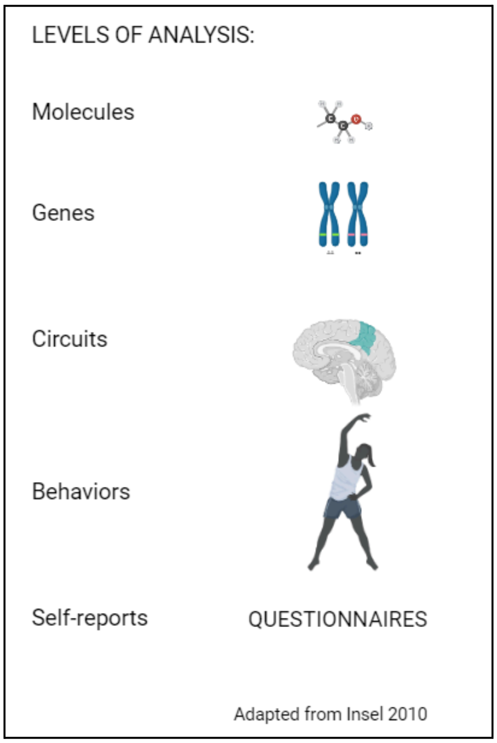
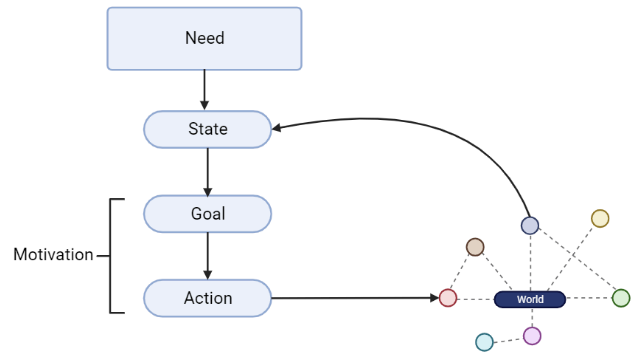


Figure 1. Level of analysis.

Psychological motivational theories have been historically based on questionnaires or behavior observations. The purpose of this figure is to show the likely foundation of all behaviors in brain circuits, molecular interactions, and genes foundation. The purpose of this paper is to inquire about a possible better foundation for psychological theories based on neurobiological processes mainly at the circuit level. (Adapted from Insel et al., 2010).

Figure 2. Motivation definition.

Motivation is always created because of a desired goal. Neuroscientists try to understand the neural processes stimulating the selection and the action toward that goal.



The goals come from needs. Those can be physiological needs (thirst and hunger) or psychological needs (relatedness, competence, and predictability). As those needs ask to be fulfilled, they trigger a state that motivates a goal definition as a way to reach the state. The mental processes that combine goal selection and triggered action is what we call motivation.

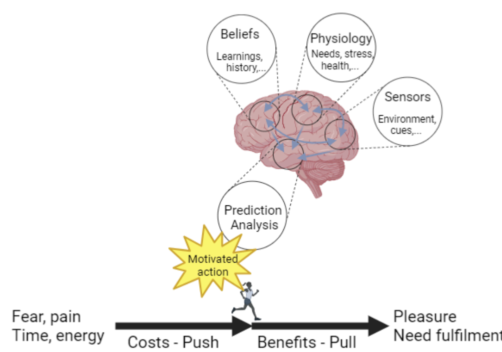


Figure 3. Behavioral neuroscience cost/benefit analysis as the source of motivated action.

Behavioral neuroscience analysis categorizes three independent variables that enter a cost-benefit analysis. The three factors influencing motivation are the organism's internal physiological states, the current environmental conditions, as well as the organism's history and experiences. The three factors enter into a cost/benefit calculation to compute the motivation. The winning goals depend greatly on the strength of the mental representation influenced by internal and external stimuli.

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